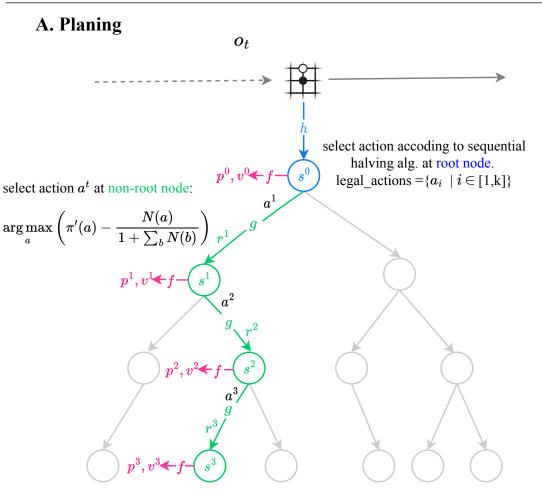
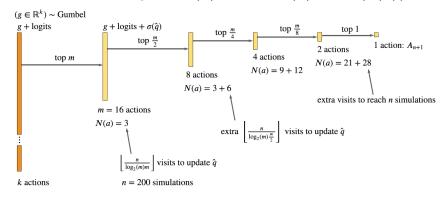
Gumbel MuZero: Planning with few simulations in high dimensional discrete action space



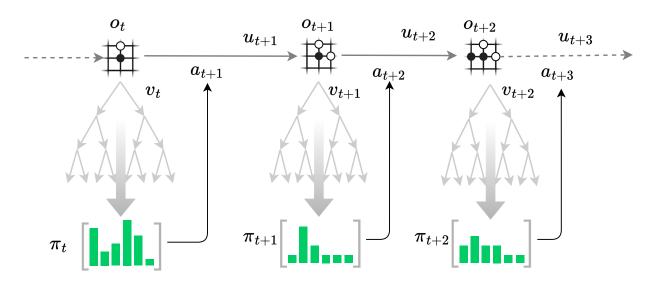
The key issue when the num of simulations n < num of total actionsk in MCTS search is how to choose which actions to vistis and how many times.

- 1. we can control the number of actions sampled without replacement.
- 2. we can use a bandit algorithm to efficiently explore the set of sampled actions.

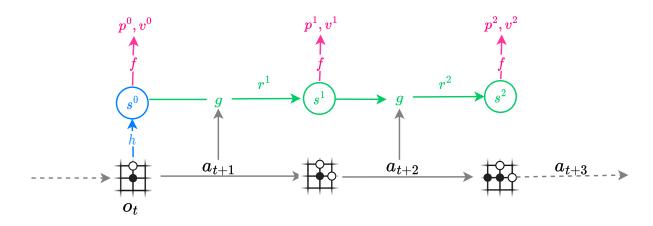
Sequential Halving is used to identify the action with the highest $g(a) + logits(a) + \sigma(\hat{q}(a))$.



B. Acting



C. Training



D. Loss

$$l_t(heta) = \sum_{k=0}^K l^r \left(u_{t+k}, oldsymbol{r_t^k}
ight) + l^v \left(z_{t+k}, oldsymbol{v_{t,mix}^k}
ight) + KL \left(oldsymbol{\pi_{t+k}'}, oldsymbol{\mathbf{p}_t^k}
ight) + c \| heta\|^2$$

mixed value approximate:
$$v_{ ext{mix}} = rac{1}{1+\sum_b N(b)} \left(\hat{v}_\pi + rac{\sum_b N(b)}{\sum_{b \in \{b:N(b)>0\}} \pi(b)} \sum_{a \in \{a:N(a)>0\}} \pi(a) q(a)
ight)$$

improved policy distribution: $\pi' = \text{softmax}(\text{logits} + \sigma(\text{completedQ}))$

$$egin{aligned} ext{completedQ}(a) = egin{cases} q(a) & ext{if } N(a) > 0 \ v_\pi, & ext{otherwise} \end{cases}$$