AlphaGo for RLers

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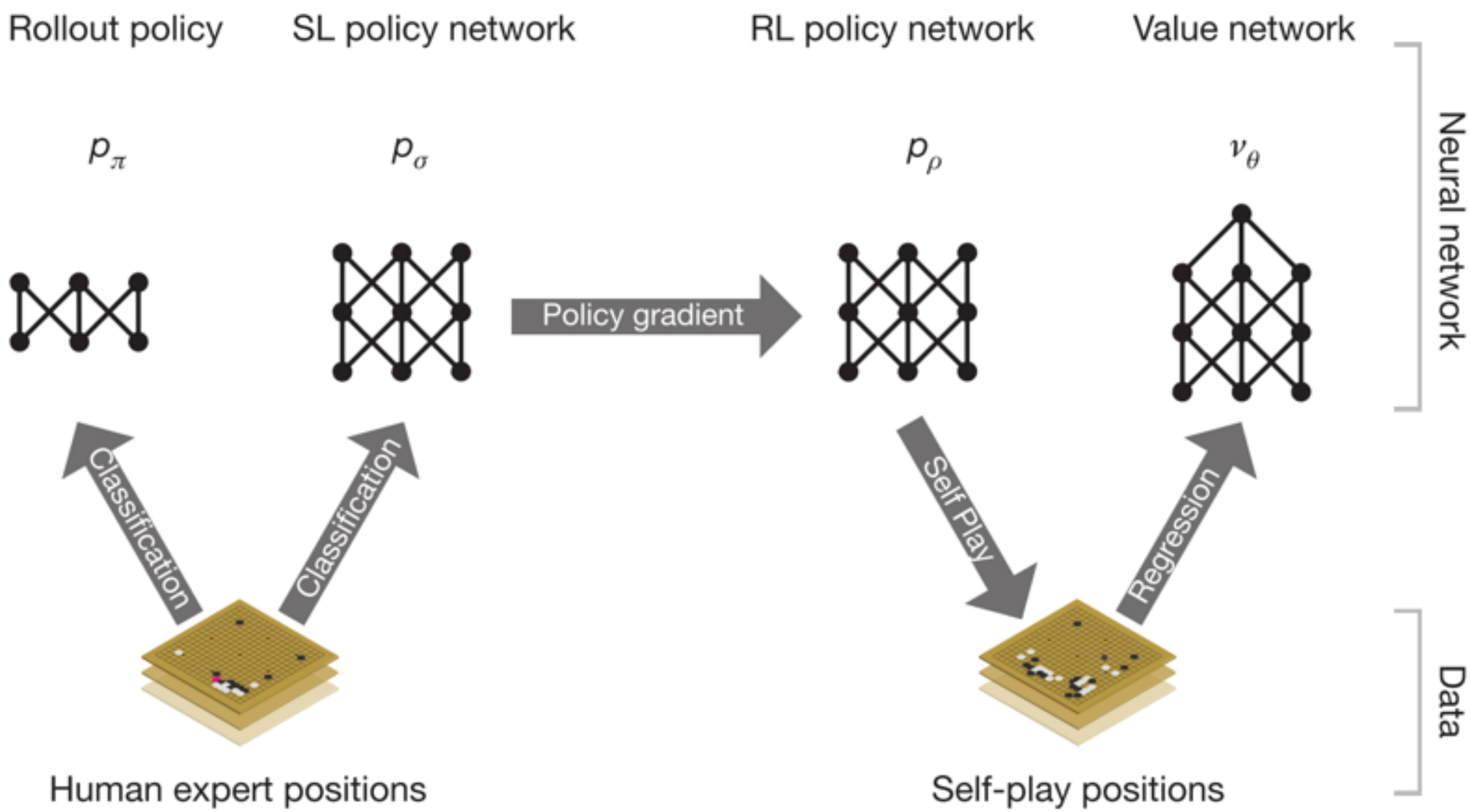
Go as an RL problem

- The complete environment model is available
  - state transition function $s' = f(s,a)$
  - reward function $r(s,a) = 0, 1$ or -1
  - terminal condition
  - we can self-play as many times as time allows
  - we can use lookahead search as long as time allows
- The opponent model is not available, but we can assume each player tries to maximize his or her return

Models in AlphaGo



SL policy network

- p_σ (s,a)
- Maximize the log-likelihood of human moves

$$\Delta\sigma = \frac{\alpha}{m}\sum_{k=1}^{m}\frac{\partial \log p_{\sigma}(a^k|s^k)}{\partial\sigma}$$

  - p_σ is computed by a softmax layer (Gibbs policy)
  - 30M positions from KGS
- Rollout policy p_π is trained in a similar way with a different dataset

RL policy network

- p_ρ（ρ is initialized with σ）
- Maximize the expected return by Williams' REINFORCE

$$\Delta\rho = \frac{\alpha}{n}\sum_{i=1}^{n}\sum_{t=1}^{T^i}\frac{\partial \log p_\rho(a_t^i|s_t^i)}{\partial\rho}(z_t^i - v(s_t^i))$$

  - v(s) is a baseline, added to reduce the variance of policy gradient estimation
    - zero in the first pass, v_θ in the second pass
- Opponents are randomly sampled from old parameters

Value network

- v_θ
- Training a value network = policy evaluation e.g. TD(λ)
  - Given a policy p_ρ, compute $v^{p_\rho}(s)$ = expected return from s
  - Assume both players follow p_ρ
- We can use Monte-Carlo estimation by repeating simply following p_ρ and observing a return
  - They observed that training on every position in a game lead to overfitting because they are strongly correlated
  - So, they created a new dataset by sampling only one state from each game

Dataset creation

- Repeat 30M times:
  - Start from an empty board s_1
  - Follow p_σ at s_1,…, s_{U-1}, U ~ unif(1,450)
  - Select a move uniformly at random at s_U
  - From s_{U+1}, follow p_ρ till the end and we can observe a return r
  - Add (s_{U+1}, r) to the dataset
- Now we have 30M i.i.d. datasets for training a value function by minimizing squared errors

$$\Delta\sigma = \frac{\alpha}{m}\sum_{k=1}^{m}(z^k - v_\theta(s^k))\frac{\partial v_\theta(s^k)}{\partial\theta}$$

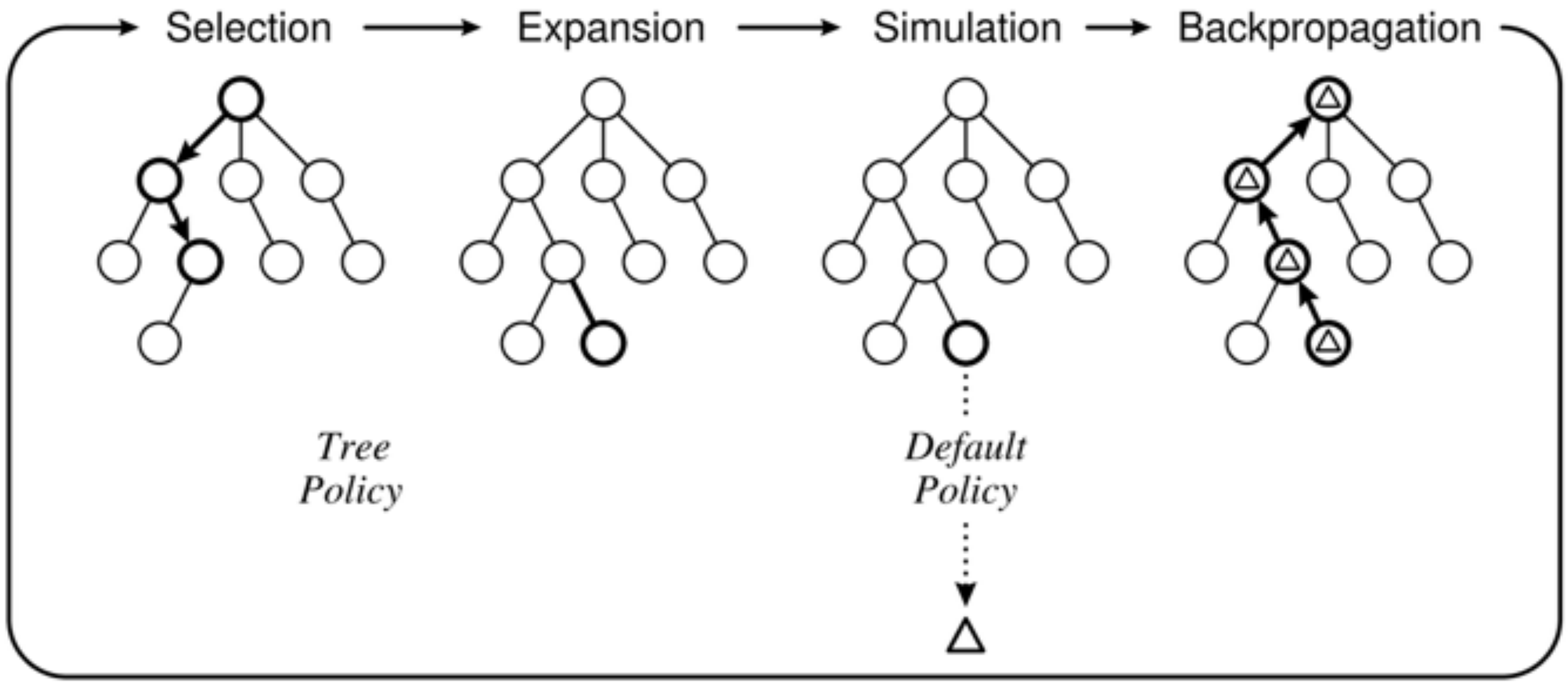
Why not TD learning?

- They don't mention it
- Monte-Carlo estimation (=TD(1)) has no bias but high variance
- TD learning (=TD(λ) with λ<1) has low variance but some bias
    - Maybe they found this bias problematic

Why not Actor-Critic?

- They don’t mention it either :(
- Actor-Critic can simultaneously learn p(a|s) and v(s), v(s) helping training of p(a|s)
    - Is it partly because v(s) is difficult to learn compared to p(a|s)?

Monte-Carlo Tree Search

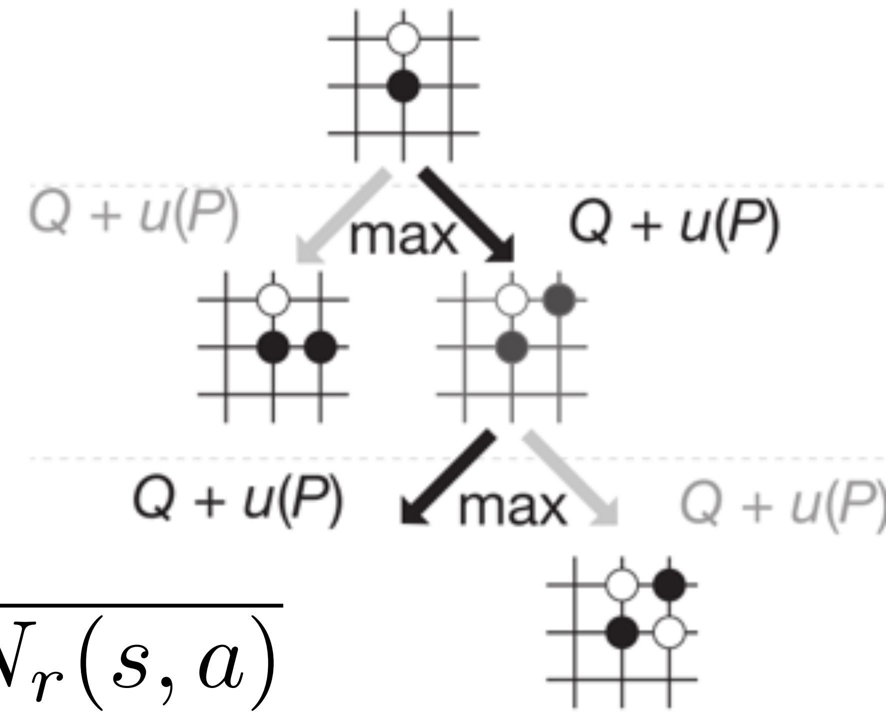


- Nodes and/or edges in a search tree hold statistics about how good they are
- Statistics are updated by backpropagating returns of simulations, so-called rollouts
- The search tree grows so that it can search promising portion of the state space more deeply

APV-MCTS

- APV stands for asynchronous policy and value
- Each node in a search tree contains edges (s,a) for all legal actions
- Each edge stores a set of statistics
  - P(s,a): prior probability (<- p_σ (s,a))
  - N_v(s,a): number of calls of v_θ below this edge
  - W_v(s,a): sum of returns of v_θ below this edge
  - N_r(s,a): number of rollouts below this edge
  - W_r(s,a): sum of returns of rollouts below this edge
  - Q(s,a): $$Q(s,a) = (1-\lambda)\frac{W_v(s,a)}{N_v(s,a)} + \lambda\frac{W_r(s,a)}{N_r(s,a)}$$

Selection



- Descend from root to leaf following:

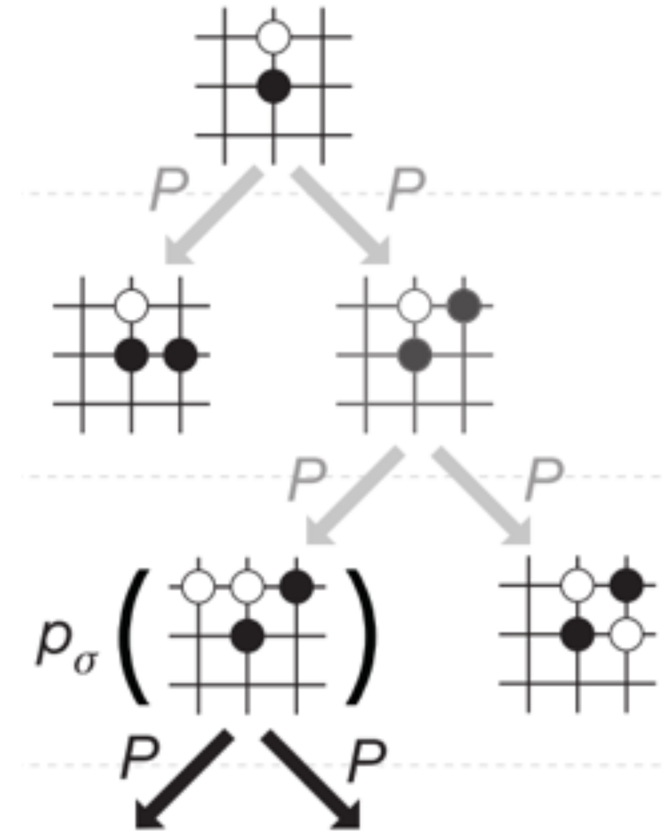
$$\mathrm{argmax}_a Q(s,a) + u(s,a)$$

$$u(s,a) = c_{\mathrm{puct}} P(s,a) \frac{\sqrt{\sum_b N_r(s,a)}}{1 + N_r(s,a)}$$

- Assign virtual loss n_vl to the statistics of selected edges so that they are not favored in other threads' selection phases
    - N_r(s,a) += n_vl, W_r(s,a) -= n_vl
- Similar but different from UCT, which is guaranteed to converge to optimal values

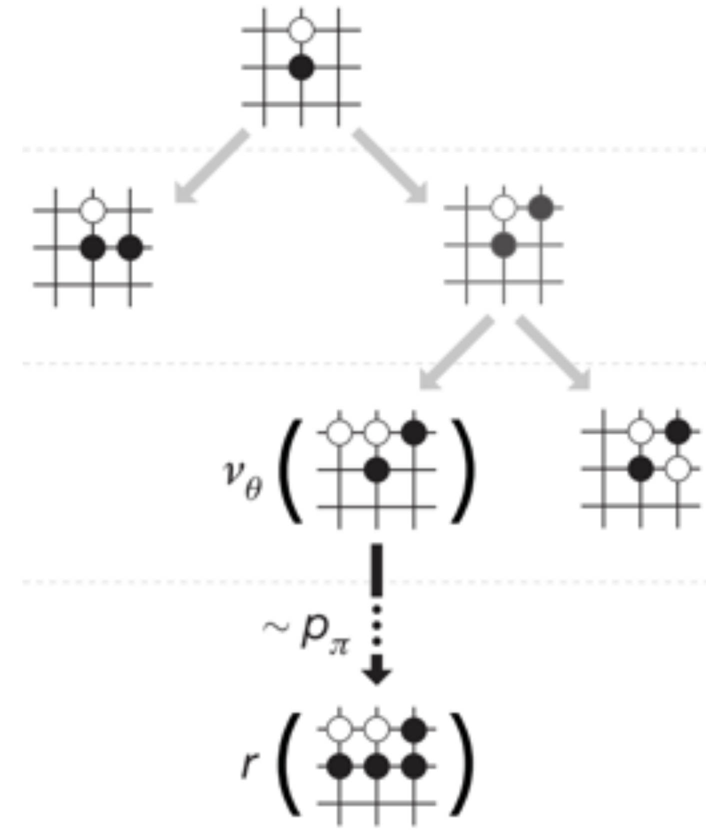
$$u_{\mathrm{uct}}(s,a) = c_{\mathrm{uct}} \frac{\sqrt{\log \sum_b N_r(s,a)}}{N_r(s,a)}$$

Expansion



- If a leaf edge's N_r(s,a) exceeds a certain threshold, add a new node
  - N_r, W_r, N_v, W_v of its edges are all initialized with 0
  - P(s,a) is initialized with outputs of SL policy network p_σ
    - They SL works better than RL here

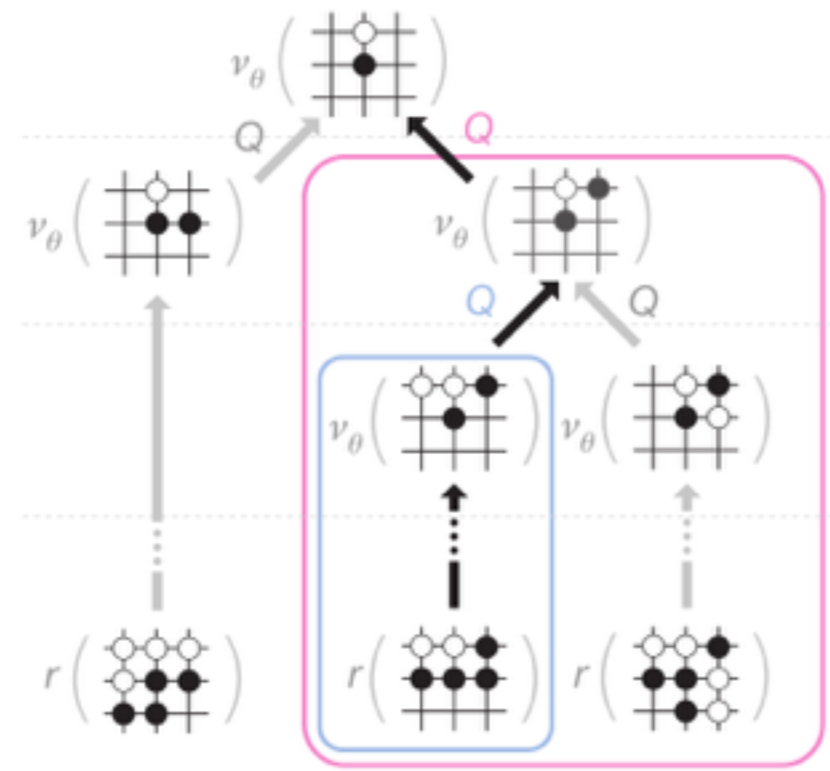
Evaluation



- If the leaf node's position s_L is not yet evaluated by v_θ, added to a queue so that it will be evaluated by v_θ asynchronously

- Simulate from s_L following p_π and observe a return r

Backup



- Update the statistics from leaf to root:
  - N_r(s,a) += 1
  - W_r(s,a) += r
- If evaluation of v_θ is complete then another backup starts asynchronously
  - N_v(s,a) += 1
  - W_r(s,a) += v_θ (s_L)

AlphaGo is strong

- As you know
- SOTA
- Beat Lee Sedol 4-1

Lessons

- Don’t fear high variance (if you have massive computation resources)
- REINFORCE can scale surprisingly well
- Using every state in an episode for training can lead to overfitting
- We still need lookahead search