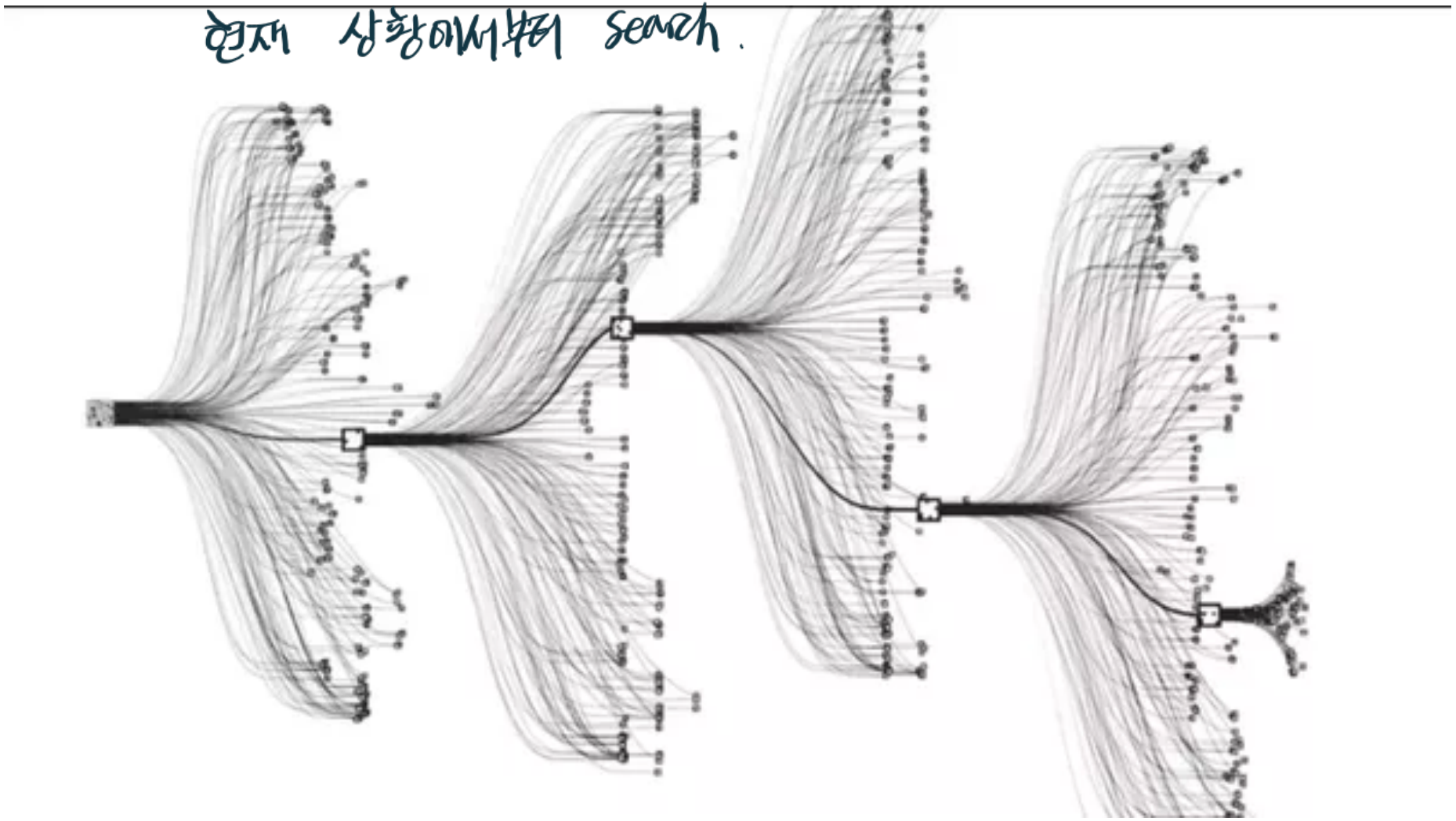
알파고1 논문 리뷰

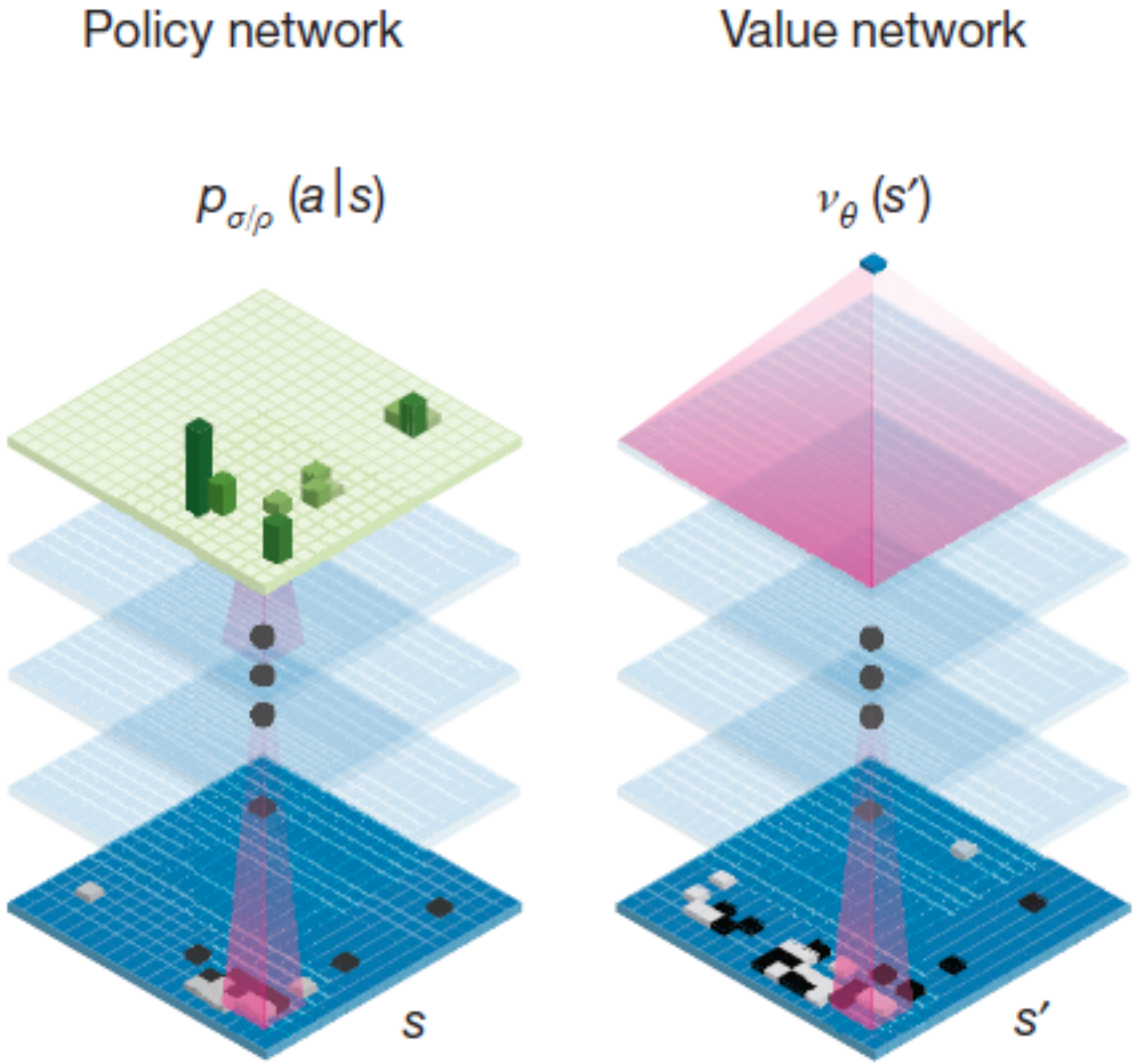
Mastering the game of Go with deep neural networks and tree search

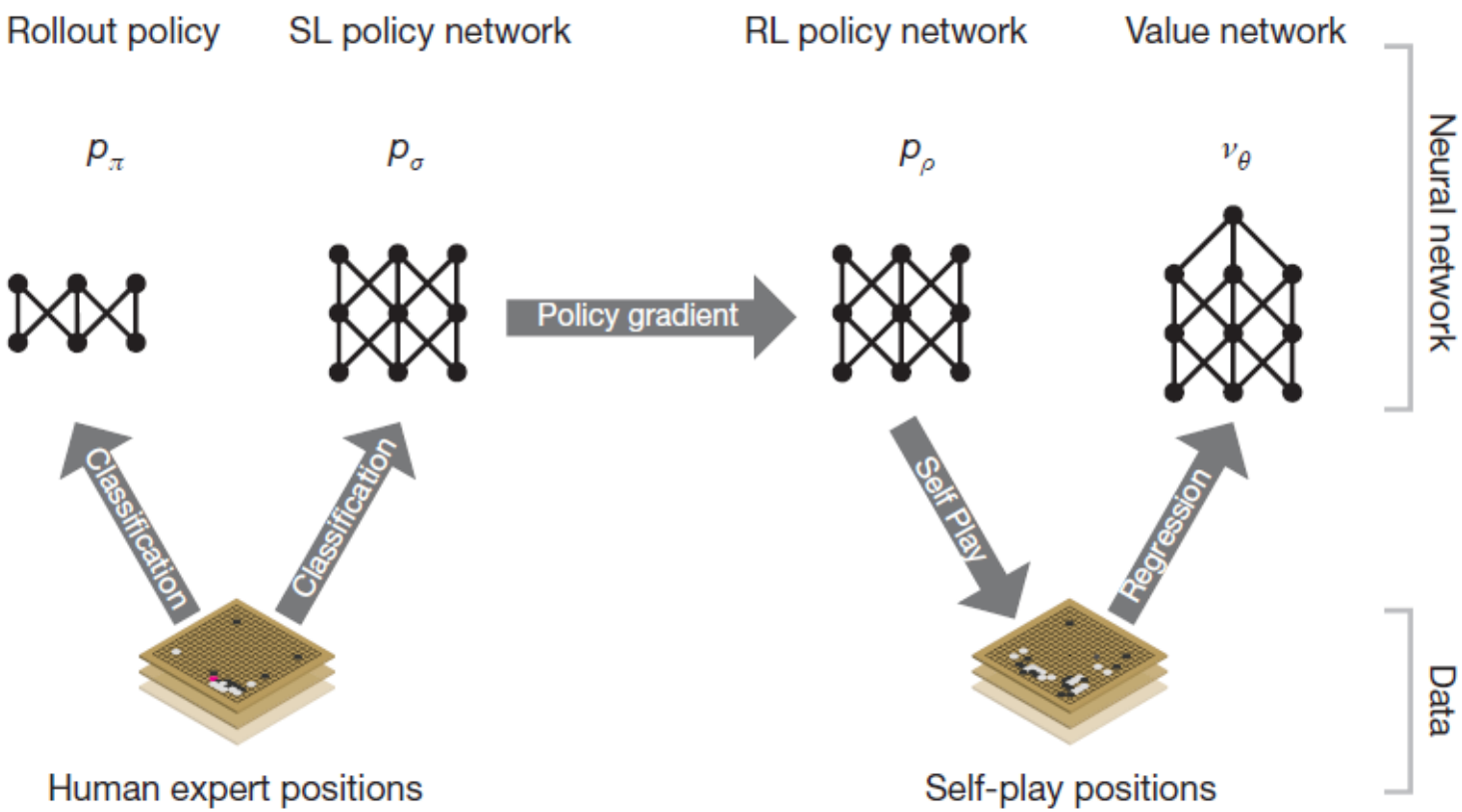
(D. Silver, A. Huang et al. 네이쳐, 2016)

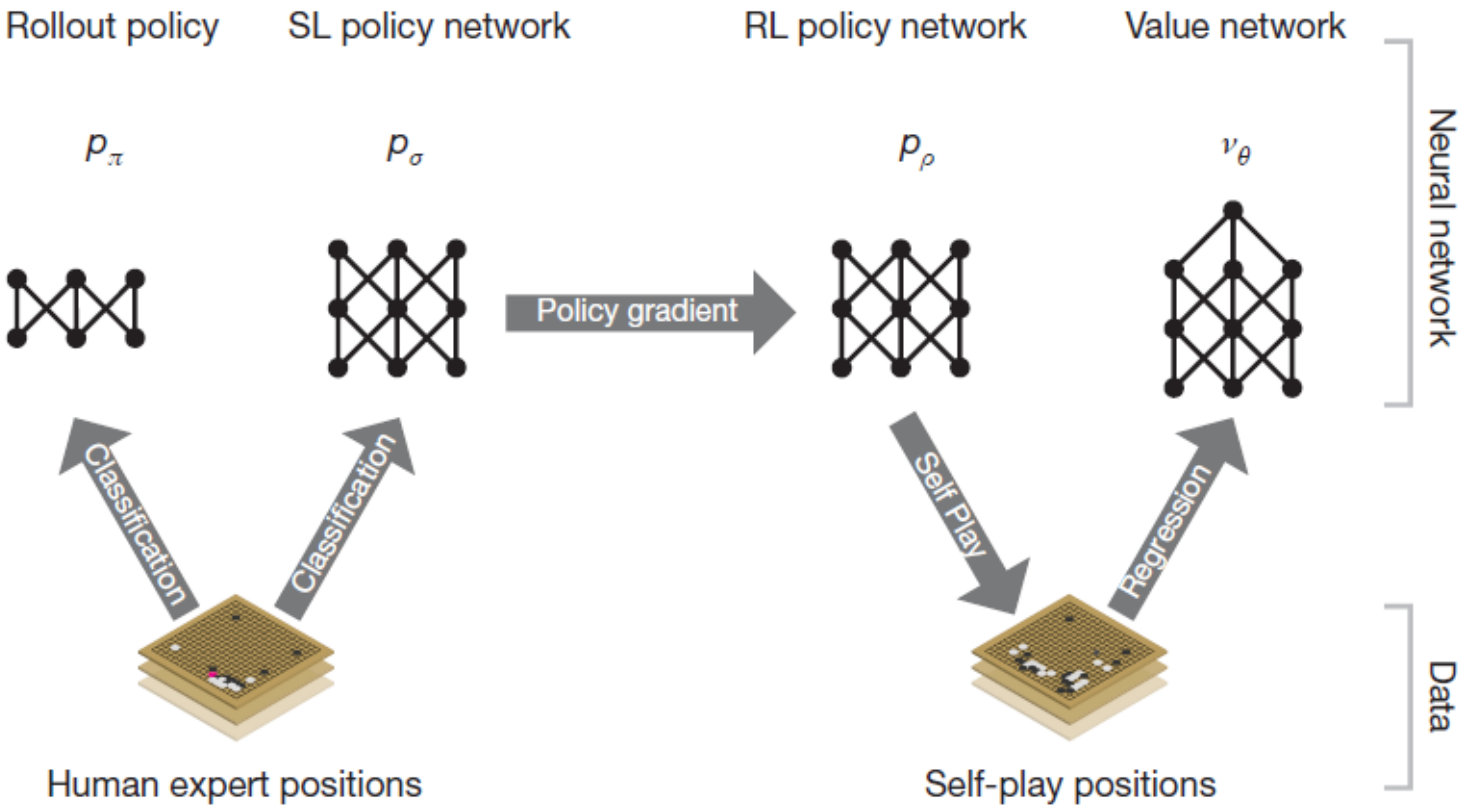
Monte Carlo Tree Search



https://blogs.loc.gov/maps/category/game-theory/

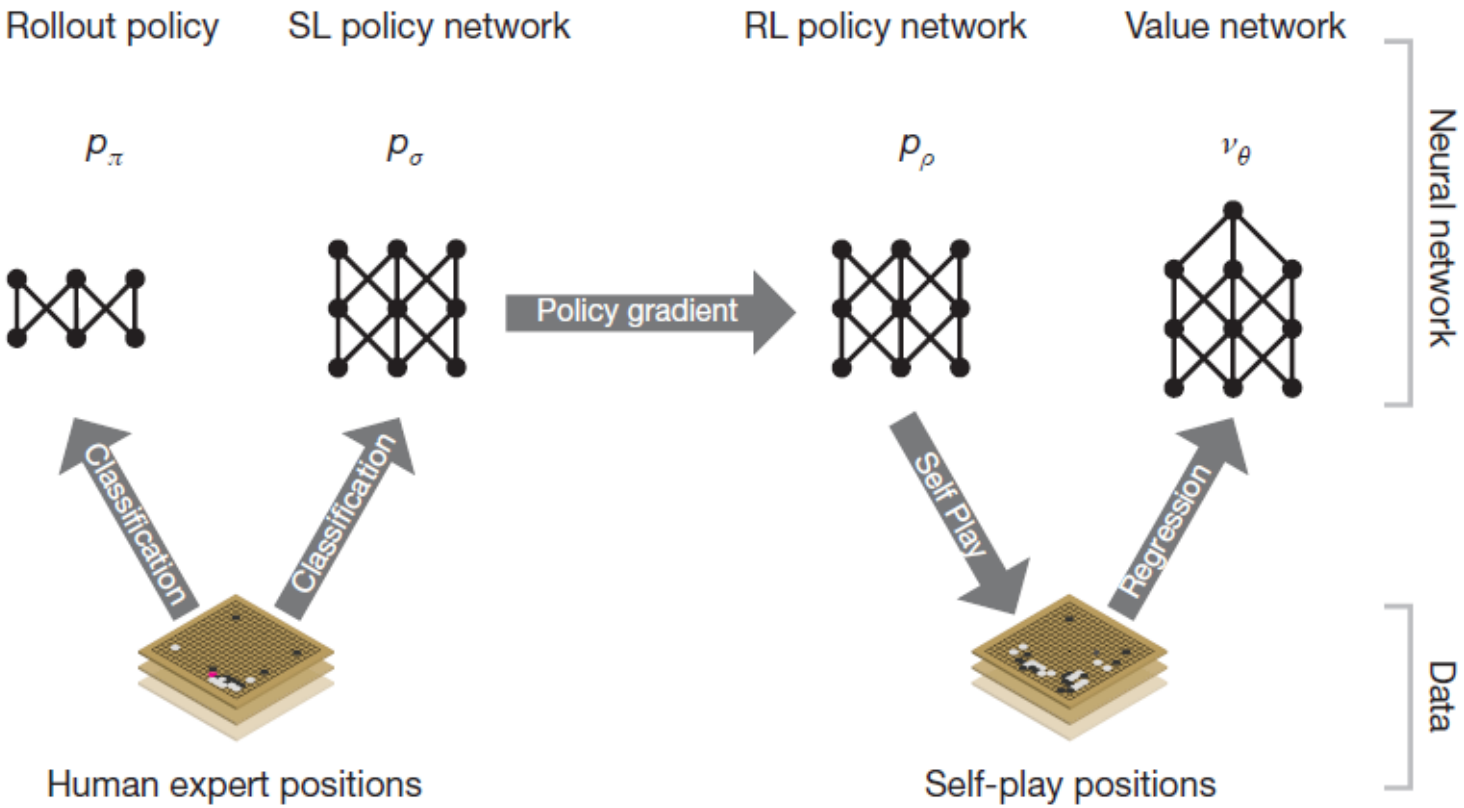

Policy network
Value network
$p_{\sigma/\rho}(a|s)$
$v_\theta(s')$
s
s'


Rollout policy
SL policy network
RL policy network
Value network
p_π
p_σ
p_ρ
v_θ
Policy gradient
Classification
Classification
Self Play
Regression
Neural network
Data
Human expert positions
Self-play positions



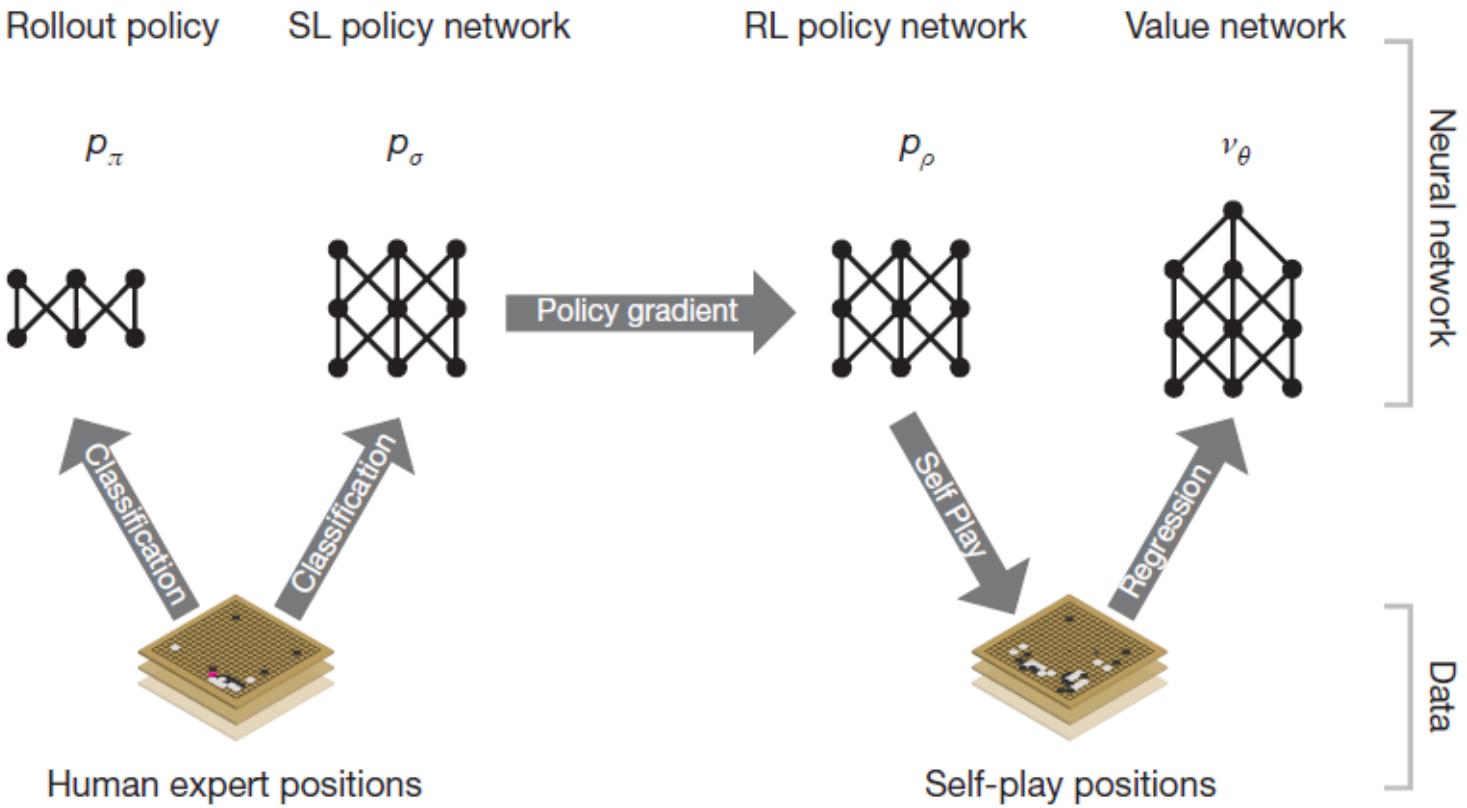
1. SL Policy

- Classification
- 13 레이어의 CNN 학습
- 인풋은 19*19*48
- 데이터 : 3천만수 (KGS 바둑 서버)
- 57% 정확도 달성 (바둑판 정보만 인풋으로 쓸 때는 55.7% 정확도)
- GPU 50개로 3주간 학습
- 3억 4천만 step



2. Rollout Policy

- 빠른 시뮬레이션을 위한 작은 네트워크
- 인풋은 Hand-crafted features
- 네트워크는 linear softmax
- 정확도는 24.2%
- 대신 action을 한번 선택하는 데 필요한 시간은 $2\mu s$ (SL Policy는 3 ms)



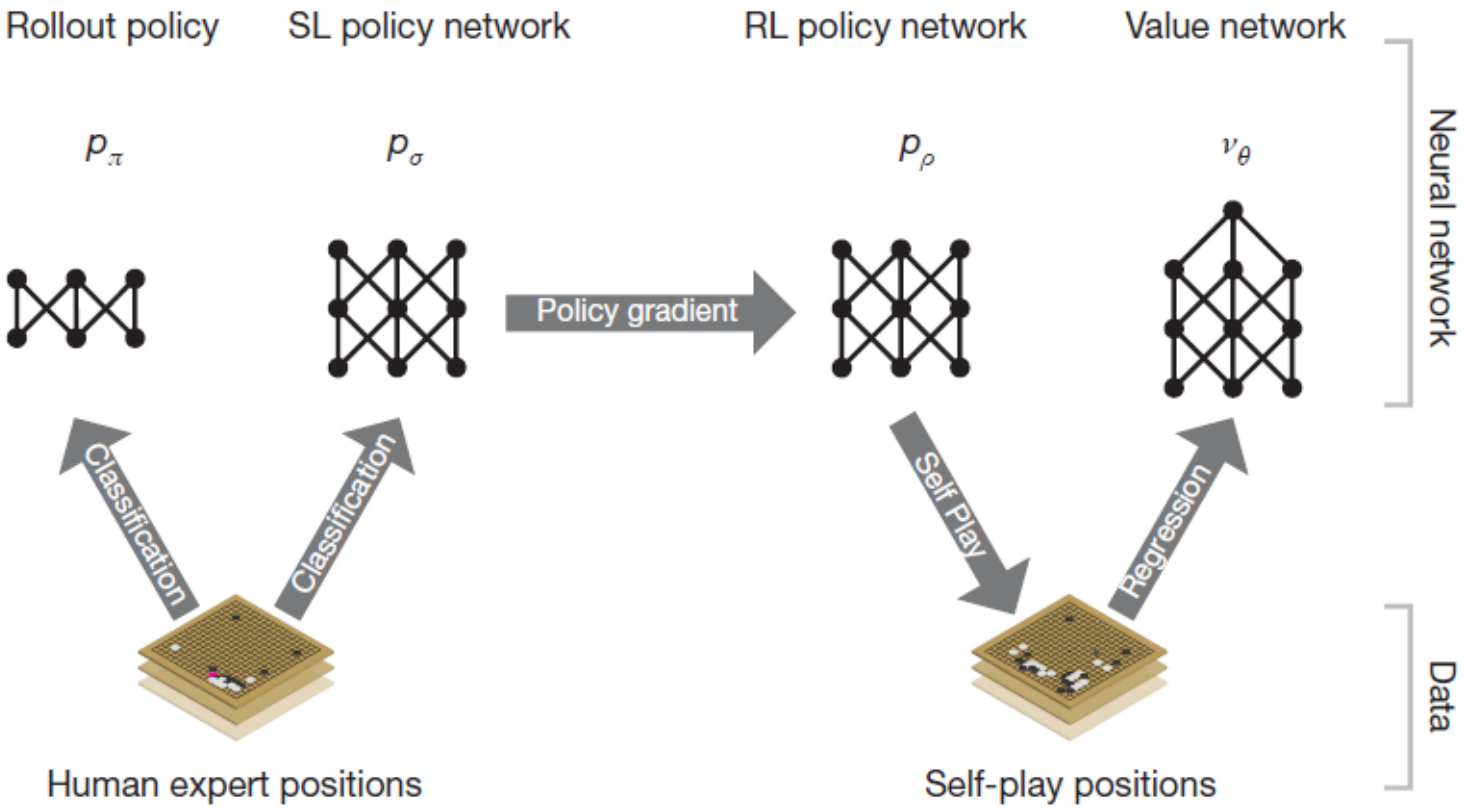
3. RL Policy

- SL Policy 와 동일한 형태의 네트워크
- 먼저 SL Policy의 weight로 초기화
- 리워드는 게임이 끝나는 시점에서만 주워지며, 이기면 +1, 지면 -1
- 알고리즘은 REINFORCE 알고리즘 사용

$$\Delta\rho \propto \frac{\partial \log p_\rho(a_t|s_t)}{\partial \rho} z_t$$

- RL vs SL ?
  RL 80% win

- GPU 50개로 1일간 학습

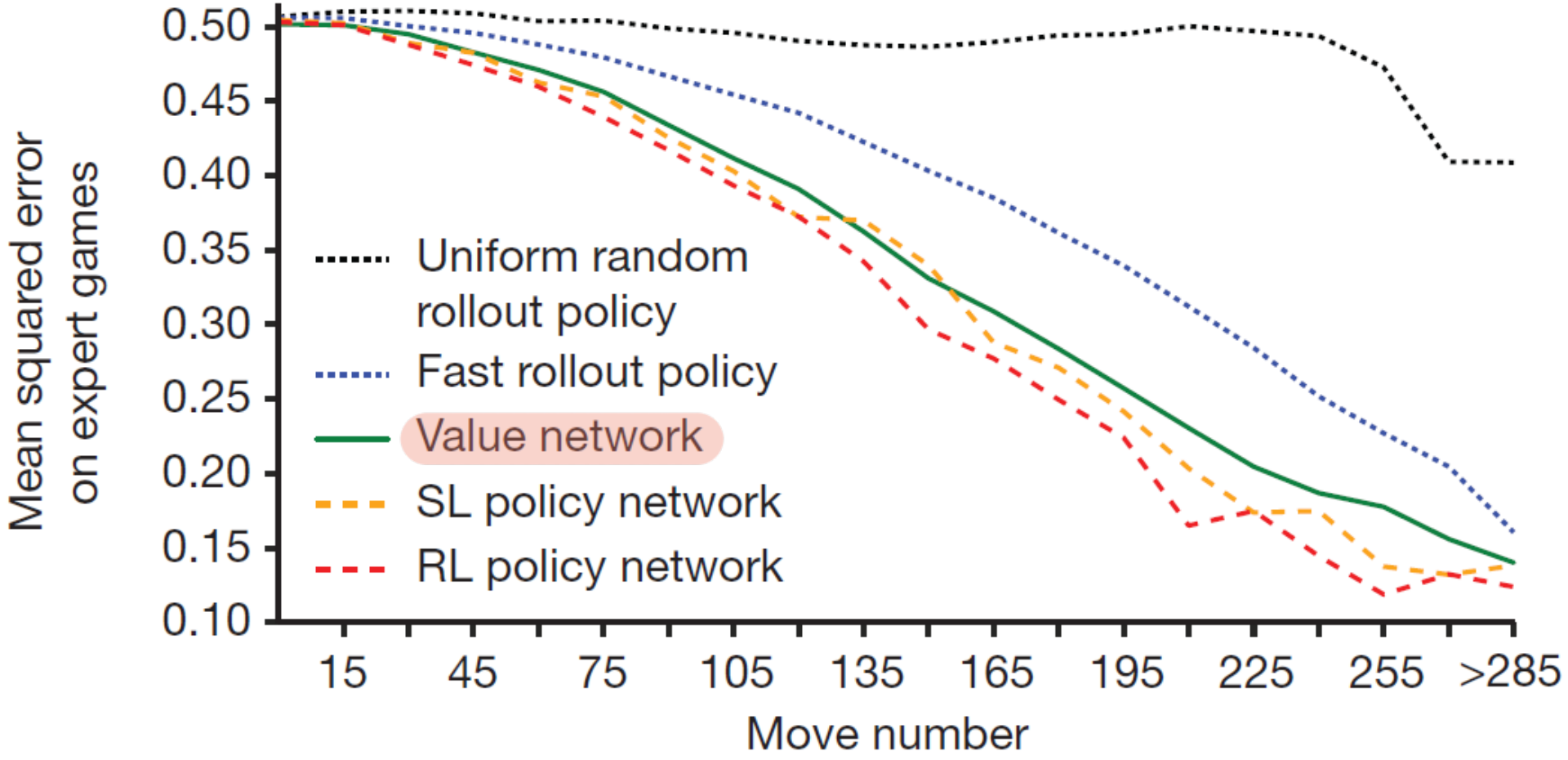


4. Value Network

- RL policy를 따랐을 때에 누가 이길지 예측하는 네트워크

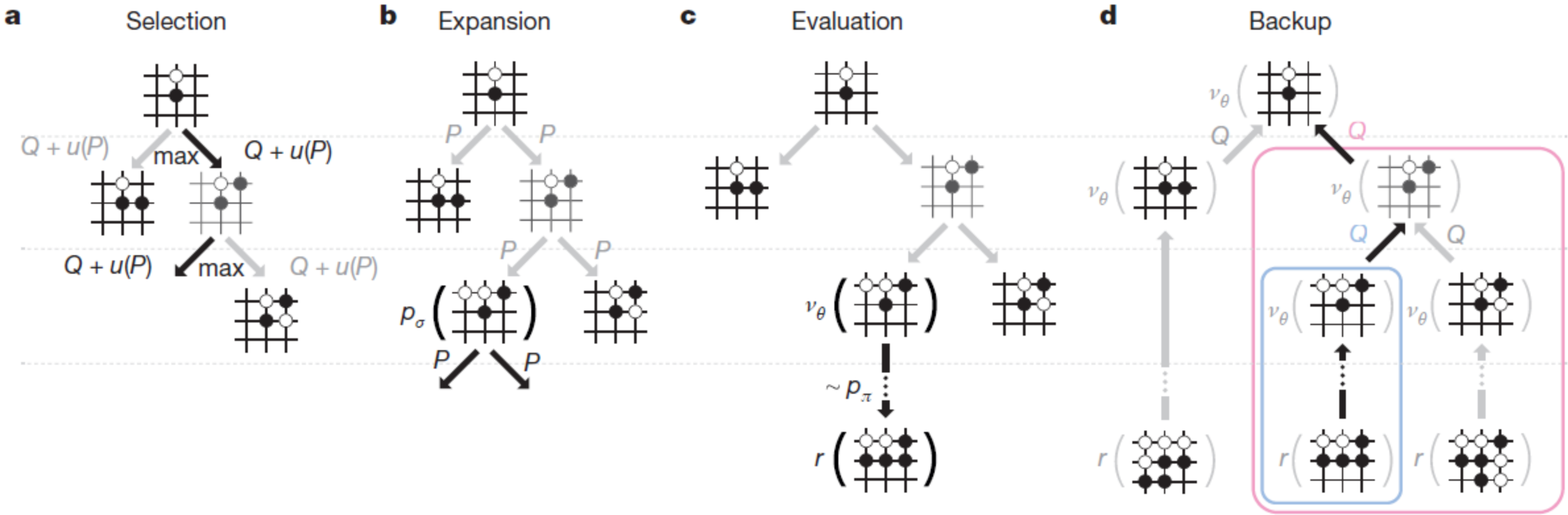
$$v^p(s) = \mathbb{E}[z_t | s_t = s,\ a_{t \ldots T} \sim p]$$

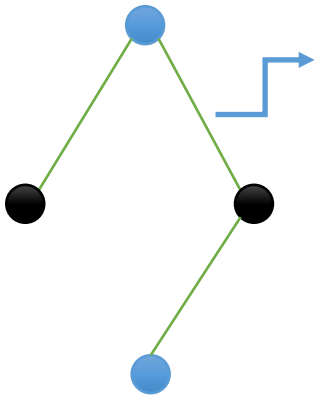
- 아랫단은 SL 네트워크와 동일 하나 윗단이 single output.
- 3천만 개의 상황으로부터 학습 (각각 다른 게임)
- GPU 50개로 1주일간 학습
- 5천만 mini-batch



- RL polic를 이용한 rollout 보다 1만5천배 빠른데, 비슷한 정확도를 보임

- value network을 학습시킴으로써 주어진 policy로 직접 둬보지 않고도 예측할 수 있다.


a
Selection
Q + u(P)
max
Q + u(P)
Q + u(P)
max
Q + u(P)
b
Expansion
P
P
P
P
p_σ
P
P
c
Evaluation
v_θ
$\sim p_\pi$
r
d
Backup
v_θ
Q
Q
v_θ
v_θ
Q
Q
v_θ
v_θ
r
r
r



For each Edge...
Q(S,A) : Action Value
N(S,A) : Visit Count
P(S,A) : Prior probability

$$a_t = \underset{a}{\operatorname{argmax}} \left(Q(s_t, a) + u(s_t, a) \right)$$

$$Q(s,a) = \frac{1}{N(s,a)} \sum_{i=1}^{n} \mathbf{1}(s,a,i) V(s_L^i)$$

$$u(s,a) \propto \frac{P(s,a)}{1+N(s,a)}$$

$$V(s_L) = (1-\lambda) v_\theta(s_L) + \lambda z_L$$

Value Network

롤아웃으로 게임을 끝까지 플레이 했을 때의 결과