CME 213

SPRING 2017

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MPI SUMMARY

- Point-to-point and collective communications
- Process mapping: across nodes and within a node (socket, NUMA domain, core, hardware thread)
- MPI buffers and deadlocks
- Blocking and non-blocking communications
- Linear algebra applications
- Groups, communicators, topologies
- Speed-up, efficiency, iso-efficiency

AlphaGo

AlphaGo

AlphaGo

- **We have seen previously the two main NNs used by AlphaGo:**
  - **Policy Network: used to predict the next move. The NN outputs a probability for each position that can be played at the next turn.**
  - **Value Network: estimate the strength of the current position, that is who is likely to win from this position.**
- **AlphaGo builds on neural networks but also uses other ideas, such as Monte-Carlo Tree Search.**

LEARNING

- Two types of learning mechanisms were used.
- **Supervised learning:** the NN for the policy network is trained to reproduce expert moves from the KGS Go server database.
- **Reinforcement learning.**
- AlphaGo plays against older versions of himself to improve the policy network.

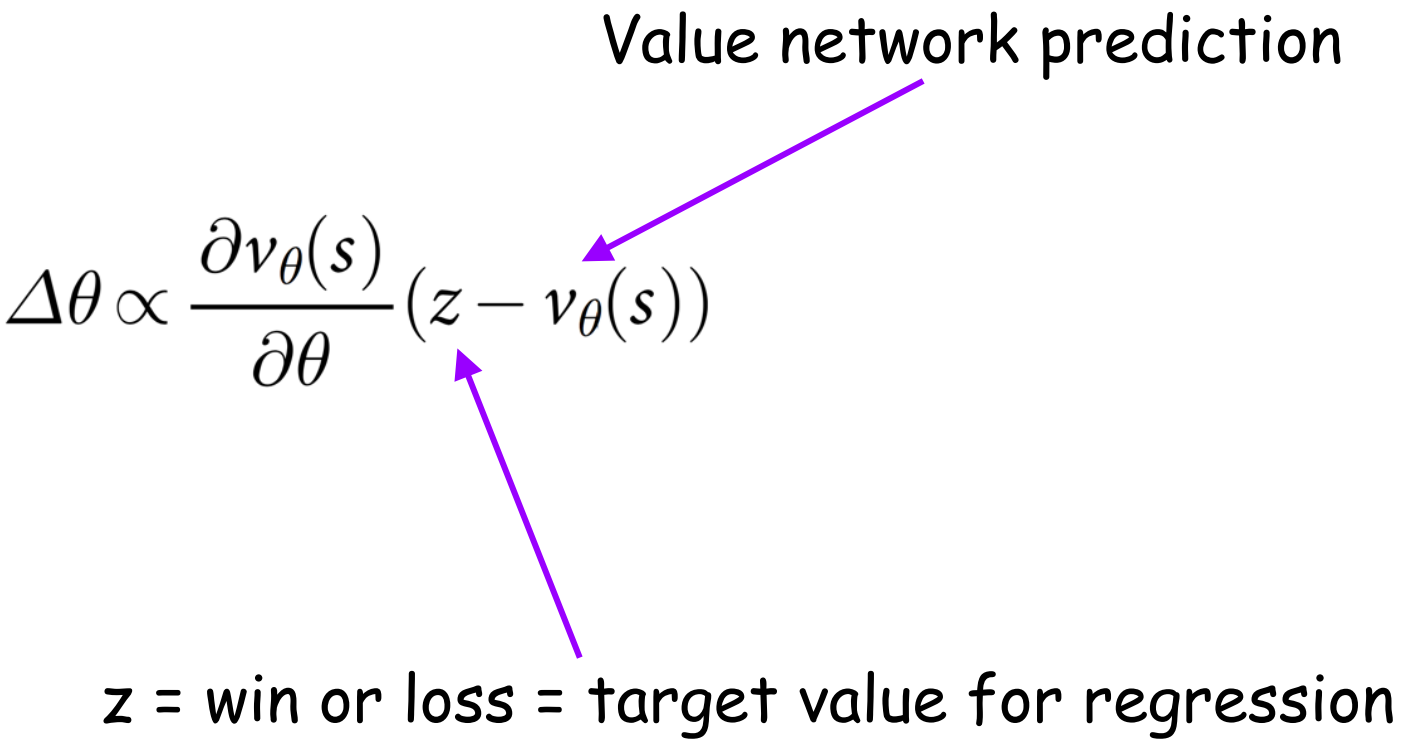
$$\Delta\rho \propto \frac{\partial \log p_\rho(a_t \mid s_t)}{\partial \rho} z_t$$

Increase probability of move

+1 if win, -1 if lose

VALUE NETWORK

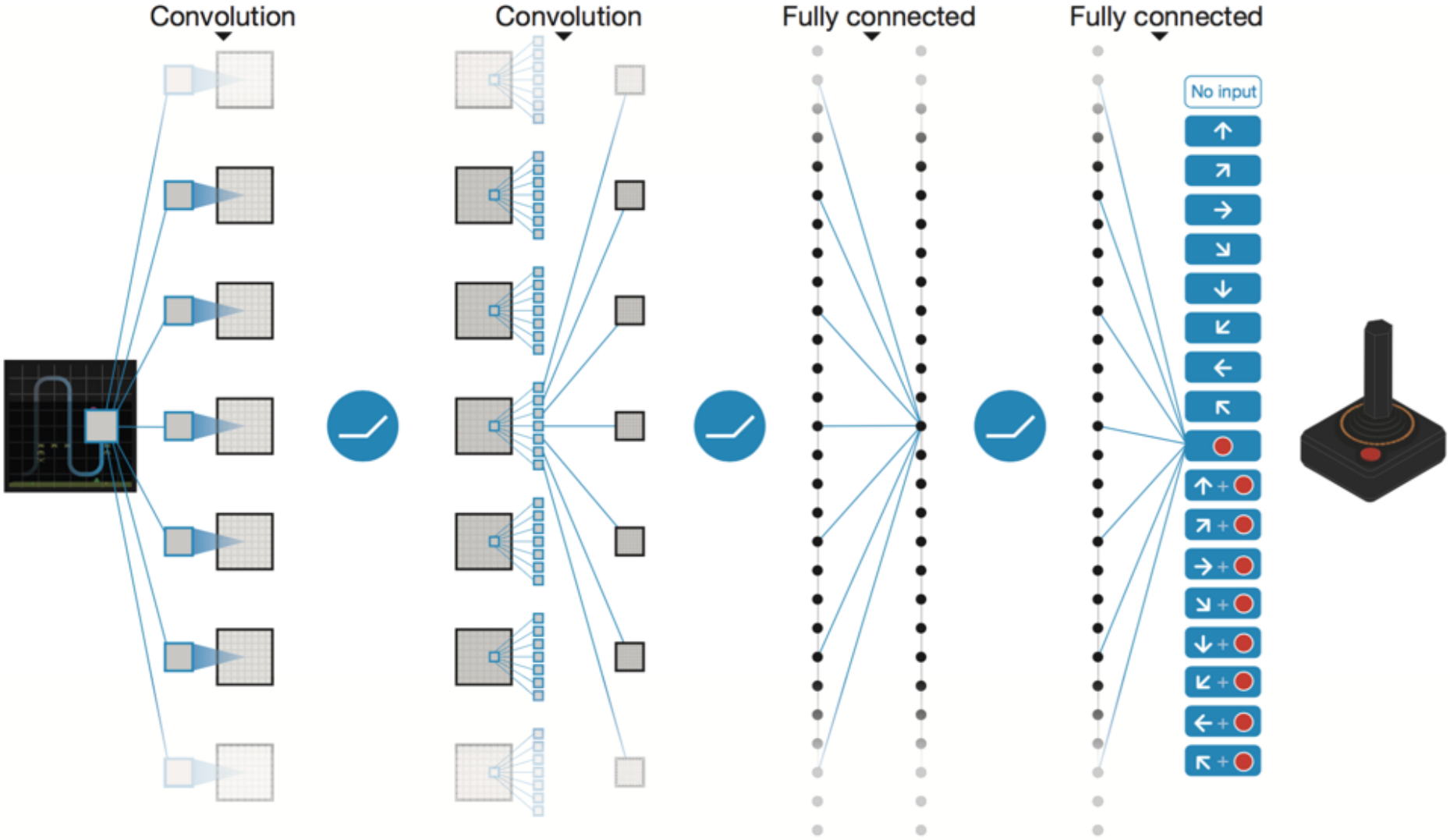
The value network is similarly updated using a regression technique.



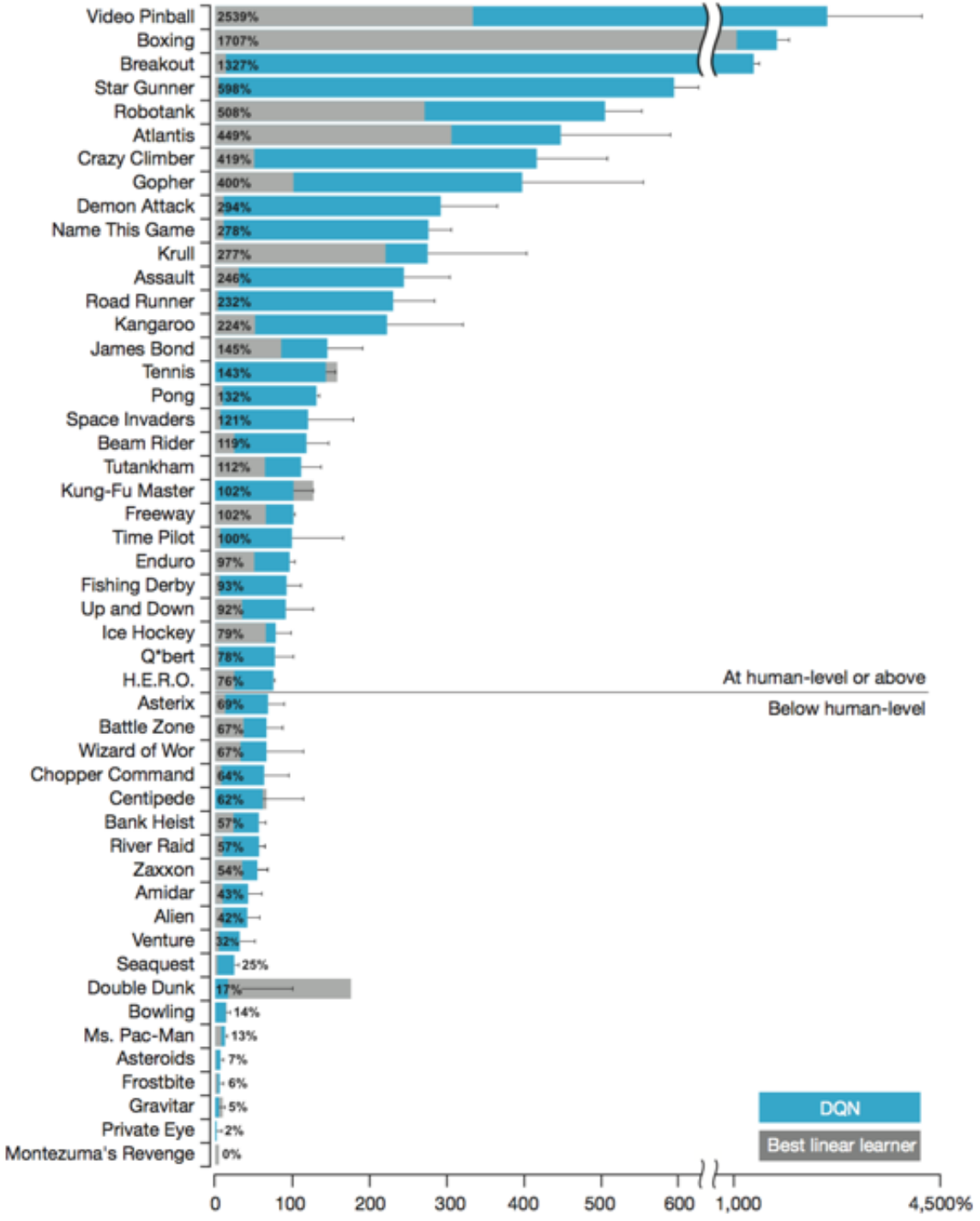
Other examples of ML for games

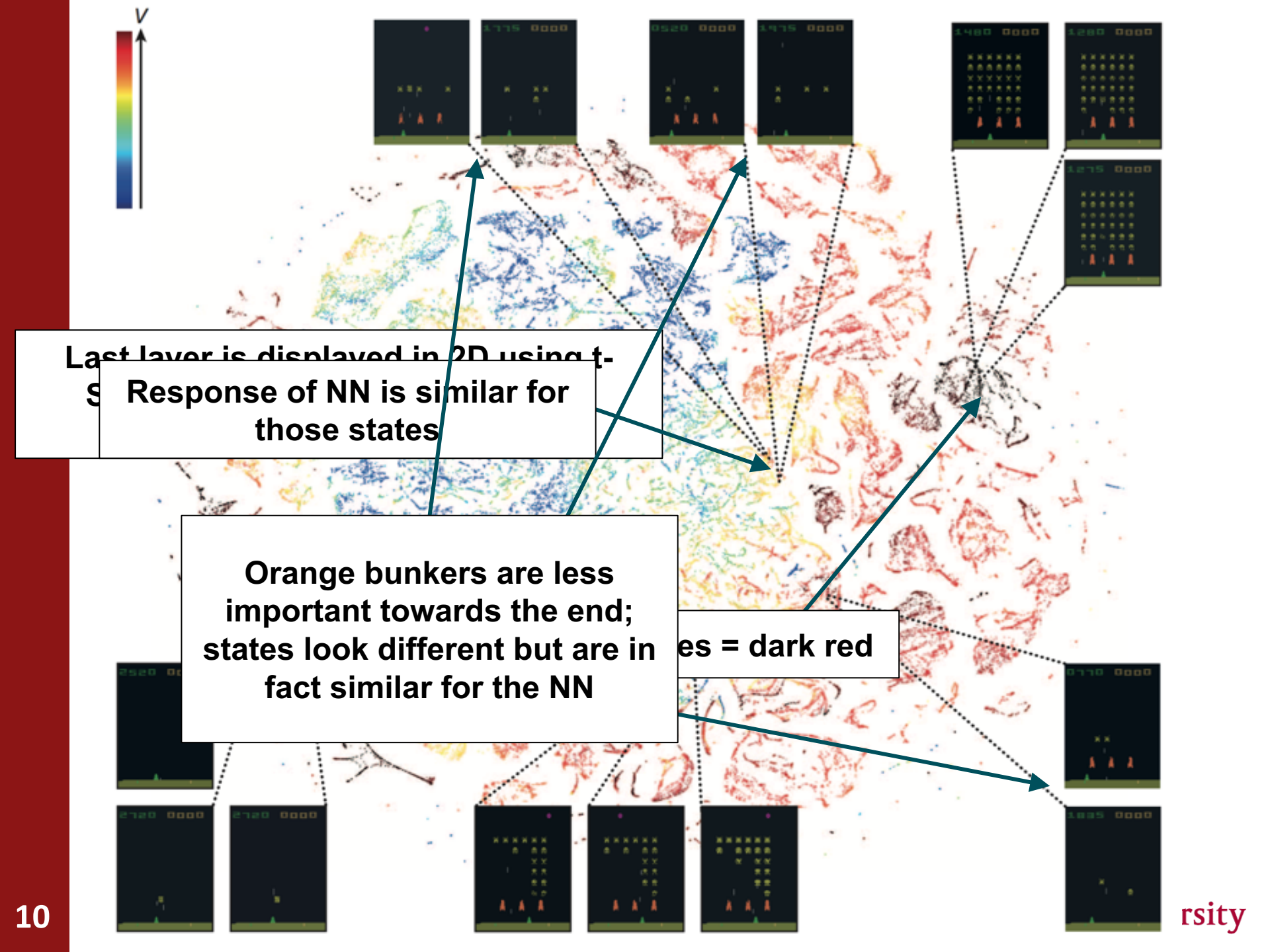
- NNs can be used for a variety of board and computer games.
- DeepRL = deep NNs with Reinforcement Learning
- DeepRL was used to master Atari 2600 games.
- DQN: Deep Q-network (Google DeepMind)
- Superhuman level was achieved using only the raw pixels and score as inputs.

SCHEMATIC VIEW OF NN



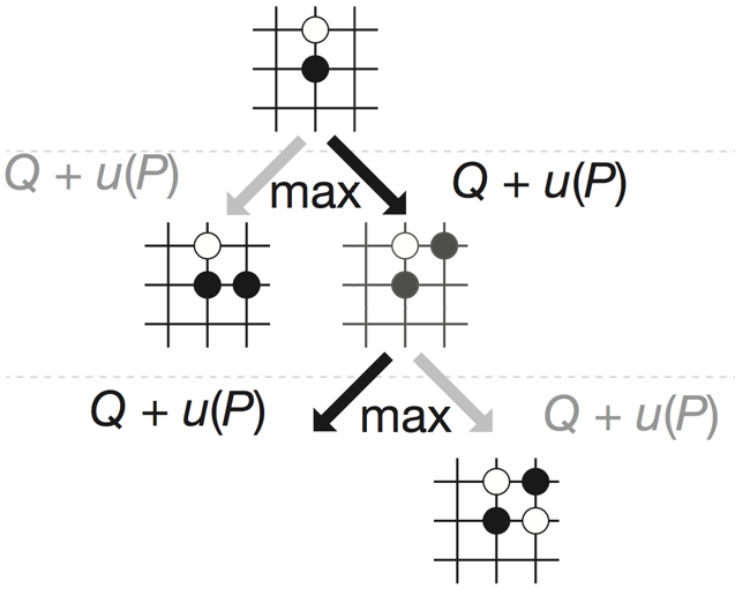
PERFORMANCE COMPARED TO HUMAN PLAYERS




V
Last layer is displayed in 2D using t-
S
Response of NN is similar for those states
Orange bunkers are less important towards the end; states look different but are in fact similar for the NN
es = dark red

NN IS NOT ENOUGH FOR GO; TREE SEARCH IS REQUIRED

- By itself, the policy network is not sufficient to achieve an accurate prediction.
- So the NN technique is coupled with a tree search algorithm.
- Tree search = search among all possible moves from the current position.
- The problem is that there are too many moves.
- So a Monte-Carlo strategy is used.



MONTE-CARLO TREE SEARCH

- **The idea is to explore the node that has the highest probability of winning.**
- **However, a strategy is in place that allows exploring other nodes as well.**
- **It's sometimes called *exploitation* and *exploration*.**
  - ***exploitation:* for a few moves with high average win rate, explore their sub-tree extensively**
  - ***exploration:* quick traversal of other nodes to make sure there is a sufficient variety of root branches being explored.**

is it better to switch from explo to exploitation?

Early

In the middle

Towards the end

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Total Results: 0

TREE TRAVERSAL

- **The next move in the tree is picked by using**

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

- **Initially, Q is 0. At convergence, Q becomes the probability that a is the best move.**

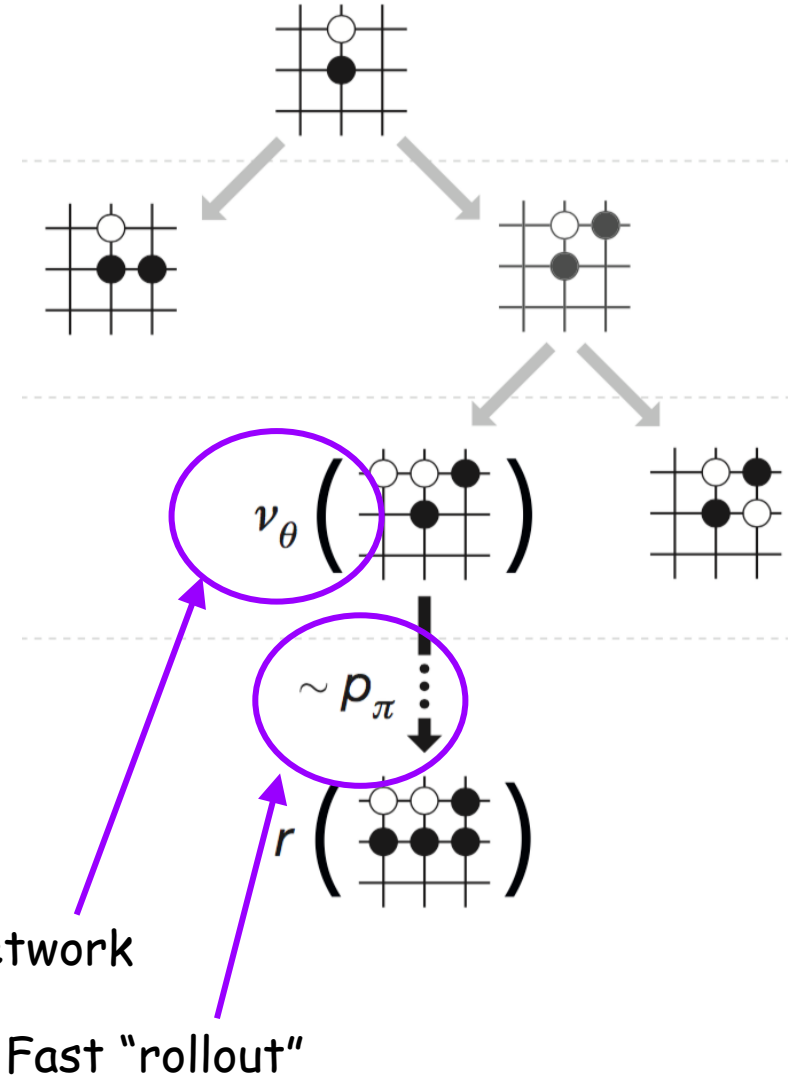
$$u(s,a) = c_{\text{puct}} P(s,a) \frac{\sqrt{\sum_b N_r(s,b)}}{1 + N_r(s,a)}$$

Number of visits

- **For nodes that are unvisited, u increases and can become large. This encourages the MCTS to visit these nodes (PUCT strategy).**
- **If they lead to a small Q, the node is ignored again. If not, the tree is further explored.**

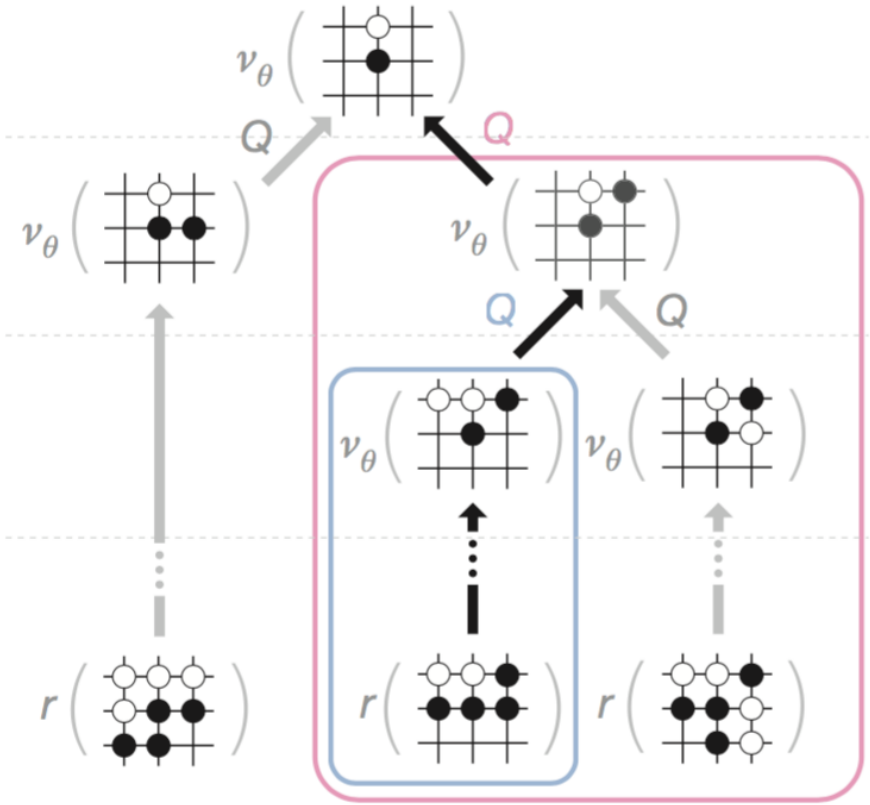
UPDATING NODE WEIGHTS

- The algorithm proceeds by visiting nodes according to the previous rule.
- When you reach a leaf, you estimate who the winner is going to be using the value network. There is also a fast procedure to run the game to the end that provides another estimate. Both are combined into a single number.



BACK UP

- **We update Q.**
- **Q is the probability that a move leads to winning the game. It is estimated using:**



Was edge (s,a) visited?

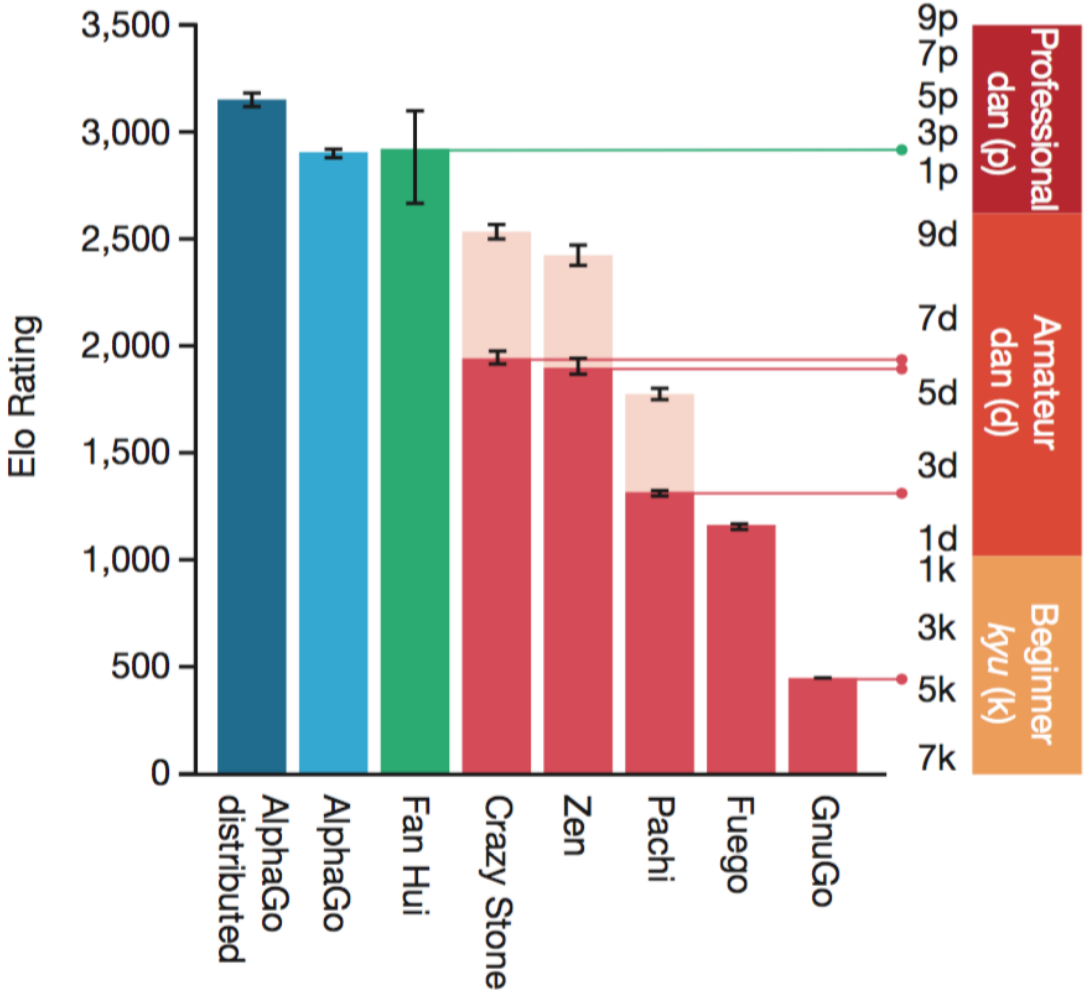
$$N(s,a) = \sum_{i=1}^{n} 1(s,a,i)$$

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

Did you win this game?

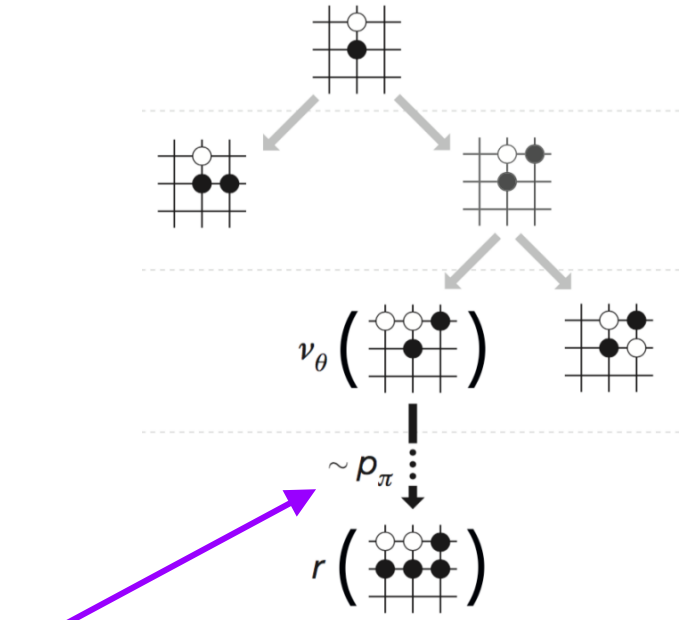
Normalization

How good is AlphaGo?



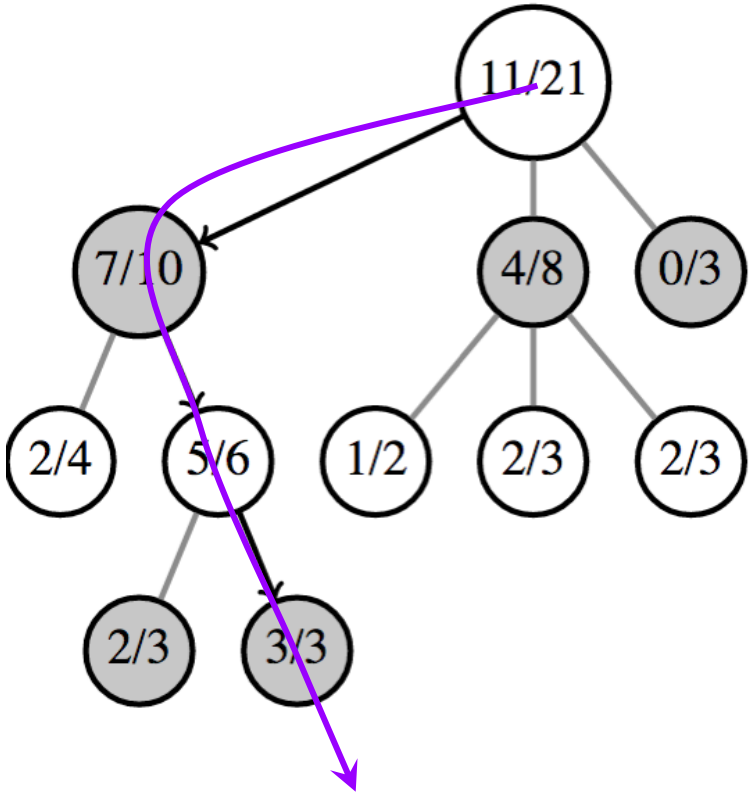
PARALLELIZATION OF MCTS

- We cover not just parallelization for AlphaGo but also general parallelization for Monte-Carlo Tree Search.
- In most MCTS, the game is played using a random strategy.
- AlphaGo uses a strategy that is only partially random: the fast random rollout to determine the winner from the current position.
- How do you distribute the work and collect in parallel the results from simulations, possibly asynchronously?



THE 4 BASIS MCTS OPERATIONS: SELECTION

- **Traverse the tree using some strategy to select the most promising moves.**
- **AlphaGo: uses argmax to find the best move.**



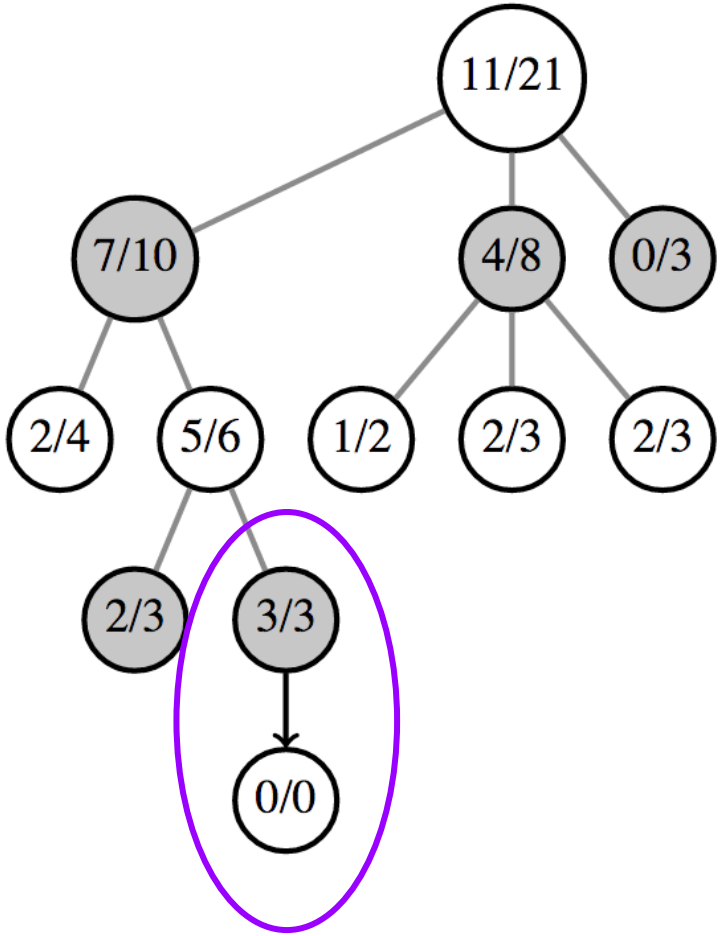
Operation 2: Expansion

Add new nodes in the tree to encourage exploration.

AlphaGo:

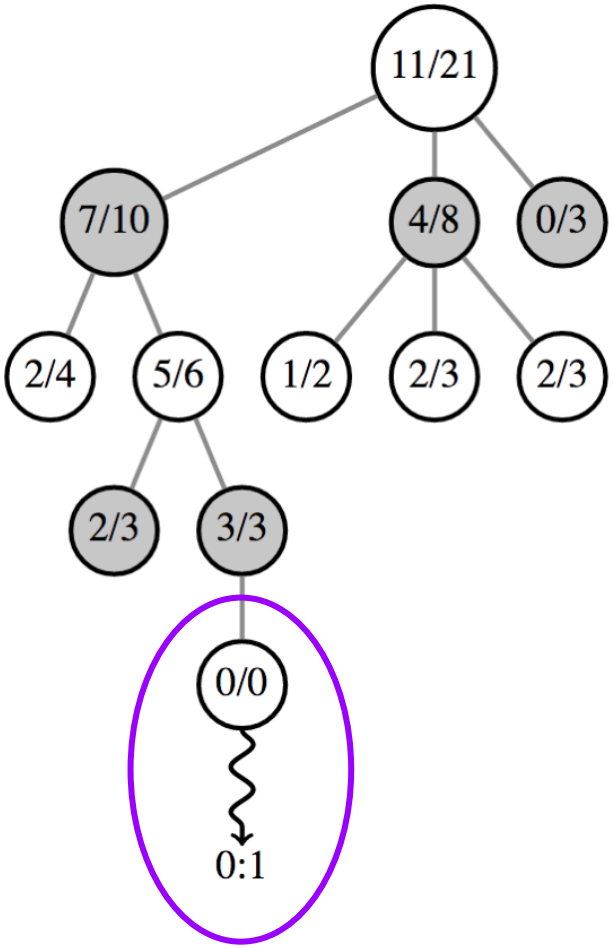
- **new nodes added depending on argmax value**
- **add a new sibling when an edge has been explored too often.**

This encourages the appearance of new nodes in the tree.



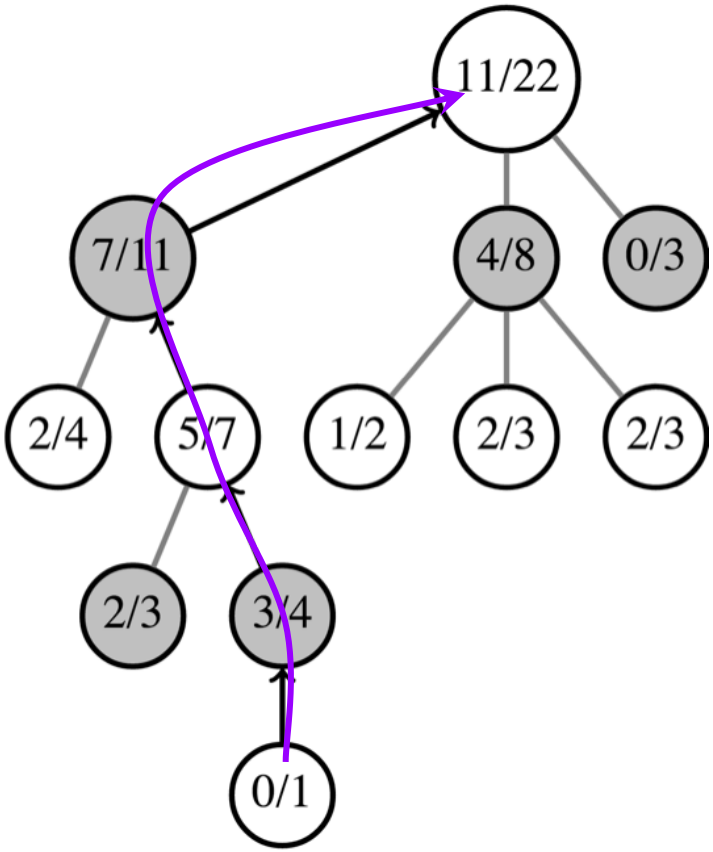
Operation 3: simulation from leaf node

- Evaluate a leaf position by playing the game from that node.
- Alphago: combination of value NN evaluation + random rollouts.



OPERATION 4: BACK PROPAGATION

Back propagate the result of the leaf simulation to update the tree.



PARALLEL STRATEGY 1: ROOT PARALLELIZATION

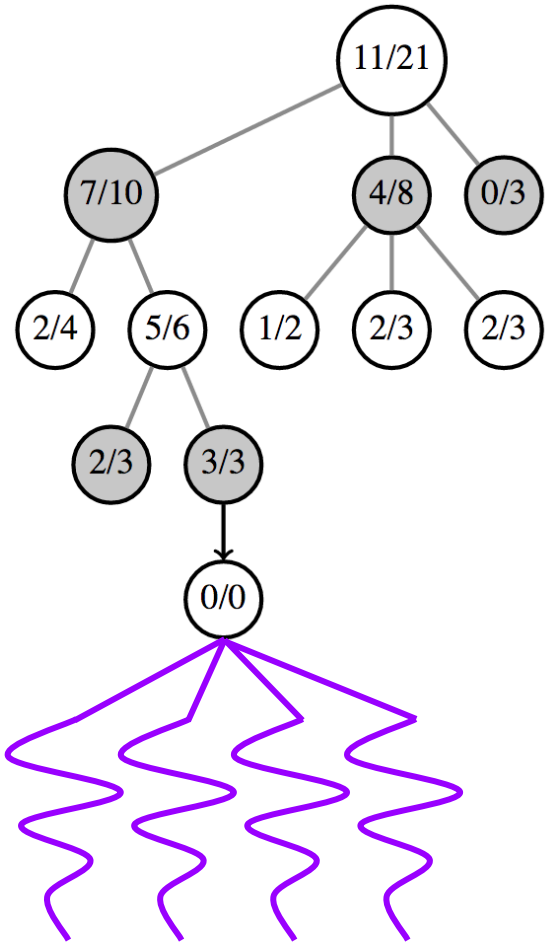
- The simplest!
- Each thread starts simulations from the root of the tree.
- Because the simulation is random, all threads traverse the tree slightly differently.
- When all simulations are complete, statistics are gathered for the root to determine the correct move.

PARALLEL STRATEGY 2: TREE PARALLELIZATION

- **The most complex!**
- **The 4 operations in MCTS are executed in parallel using mutexes.**
- **This allows accessing and updating the tree in a consistent manner.**
- **A virtual loss is sometimes used to avoid threads going down the same path.**
  - **If many threads traverse the tree at the same time, they may end up traversing the same nodes.**
  - **To avoid this, whenever a thread (call it Thread0) goes down the tree it records a fictitious loss (virtual loss).**
  - **As a result other threads tend to visit other nodes.**
  - **When Thread0 has determined the actual win or loss, it back propagates this information and corrects the virtual loss.**

PARALLEL STRATEGY 3: LEAF PARALLELIZATION

This is the closest one to AlphaGo.



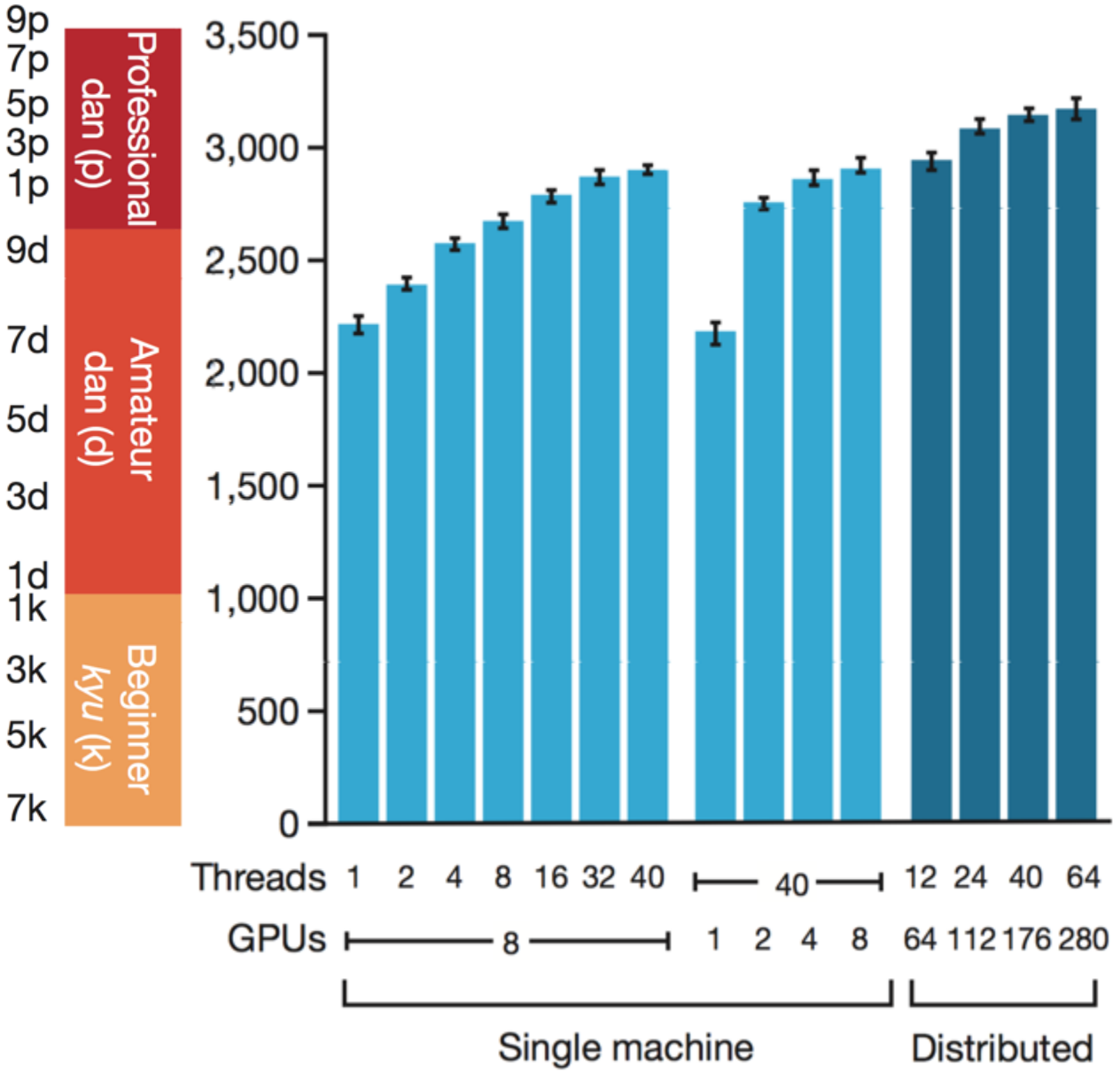
Spawn worker tasks at a leaf to evaluate the win/loss probability

AlphaGo parallelization

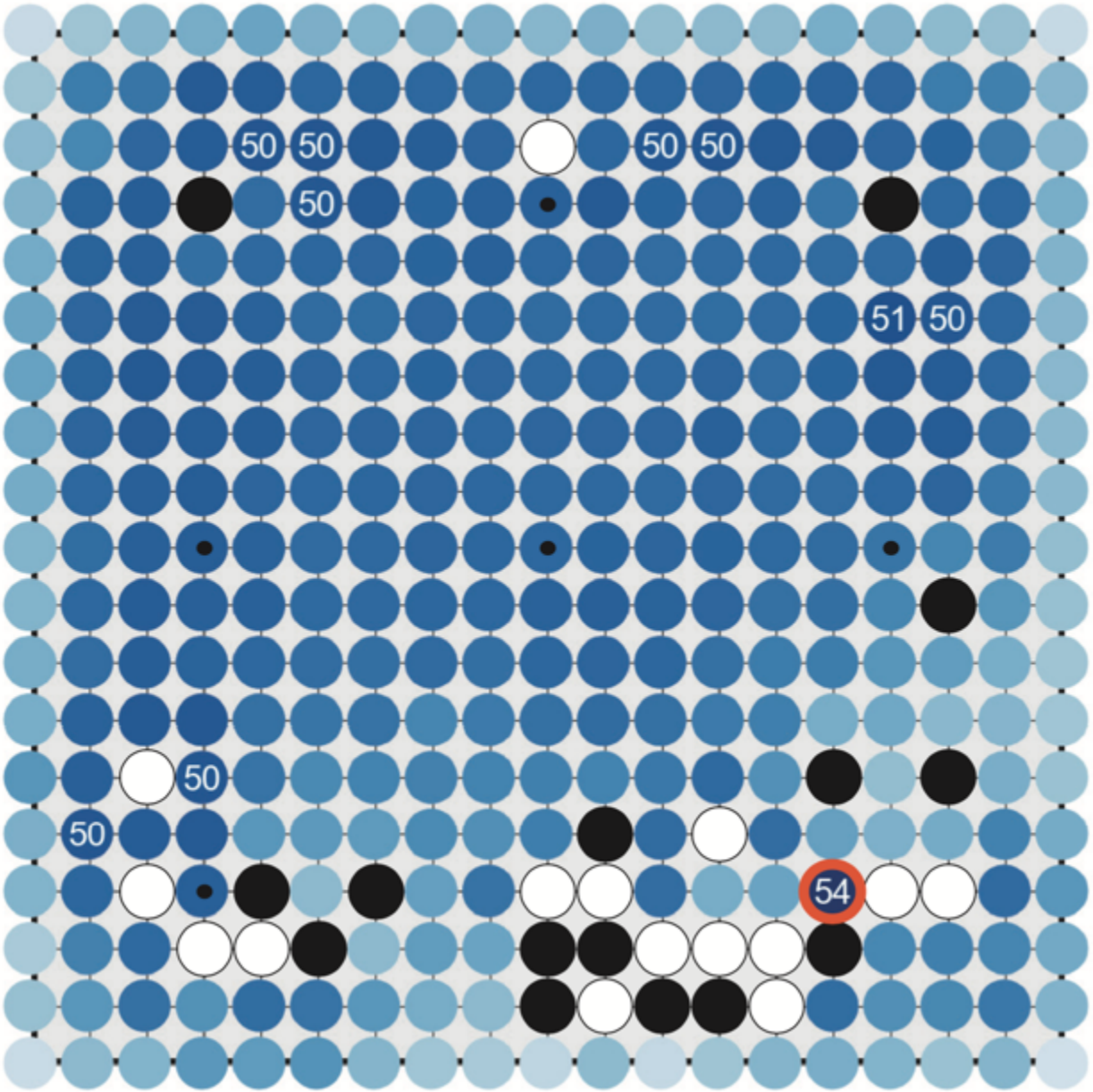
- It uses a combination of these techniques.
- A single search tree is stored on the master thread.
  - CPU: random rollouts simulations.
  - GPU: policy and value NN evaluations.
- GPUs were also used heavily to train the NNs.
- Asynchronous updates: virtual losses are used in the parallelization procedure.
  - The master thread assigns a virtual loss.
  - Then, it launches a worker task to compute the actual win/loss.
  - Once the result comes back, the tree is updated.
- This prevents too many threads from exploring the same path.

ELO OF ALPHAGO

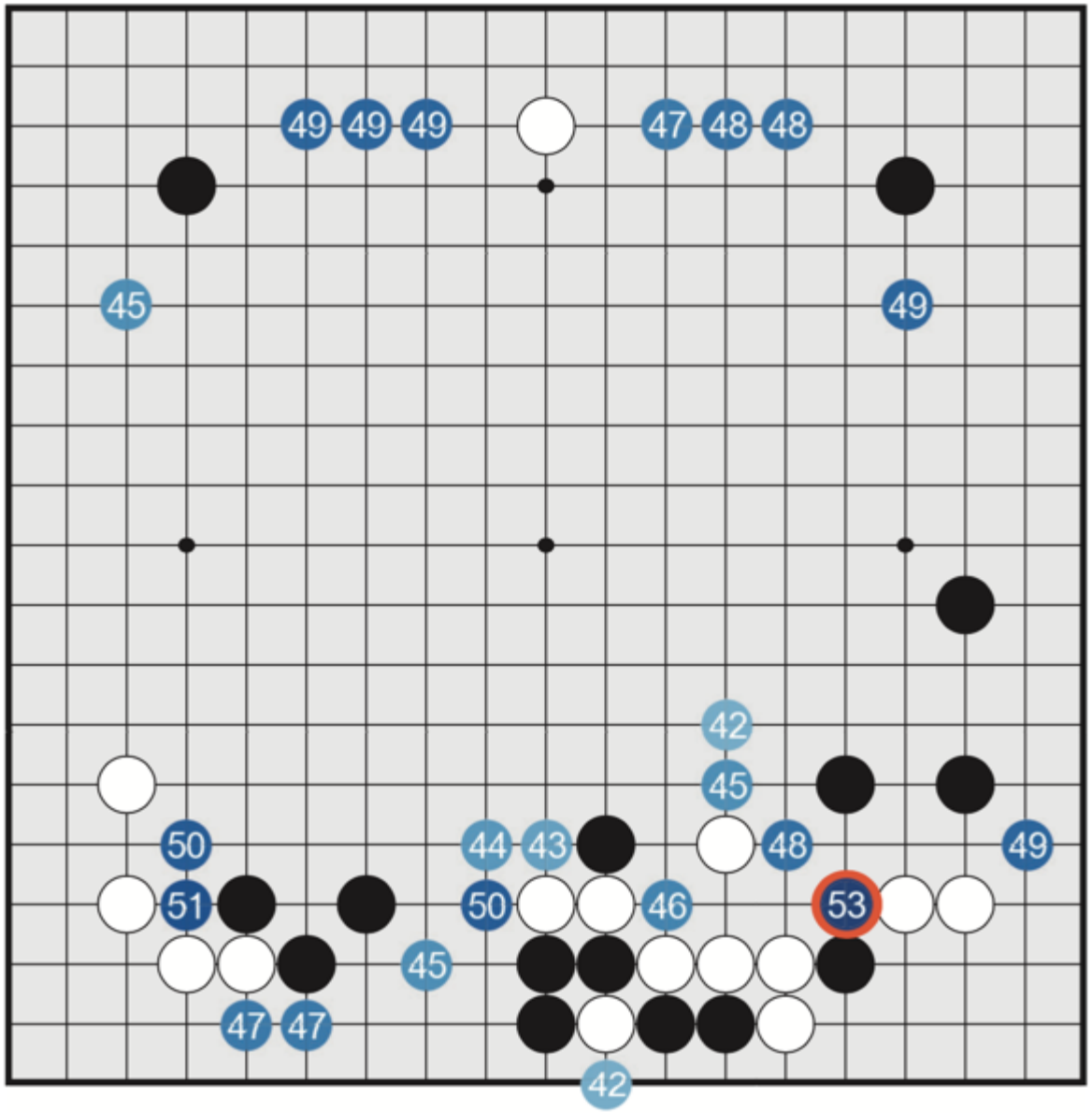
Elo rating as a function of the number of concurrent CPU cores and GPUs used.



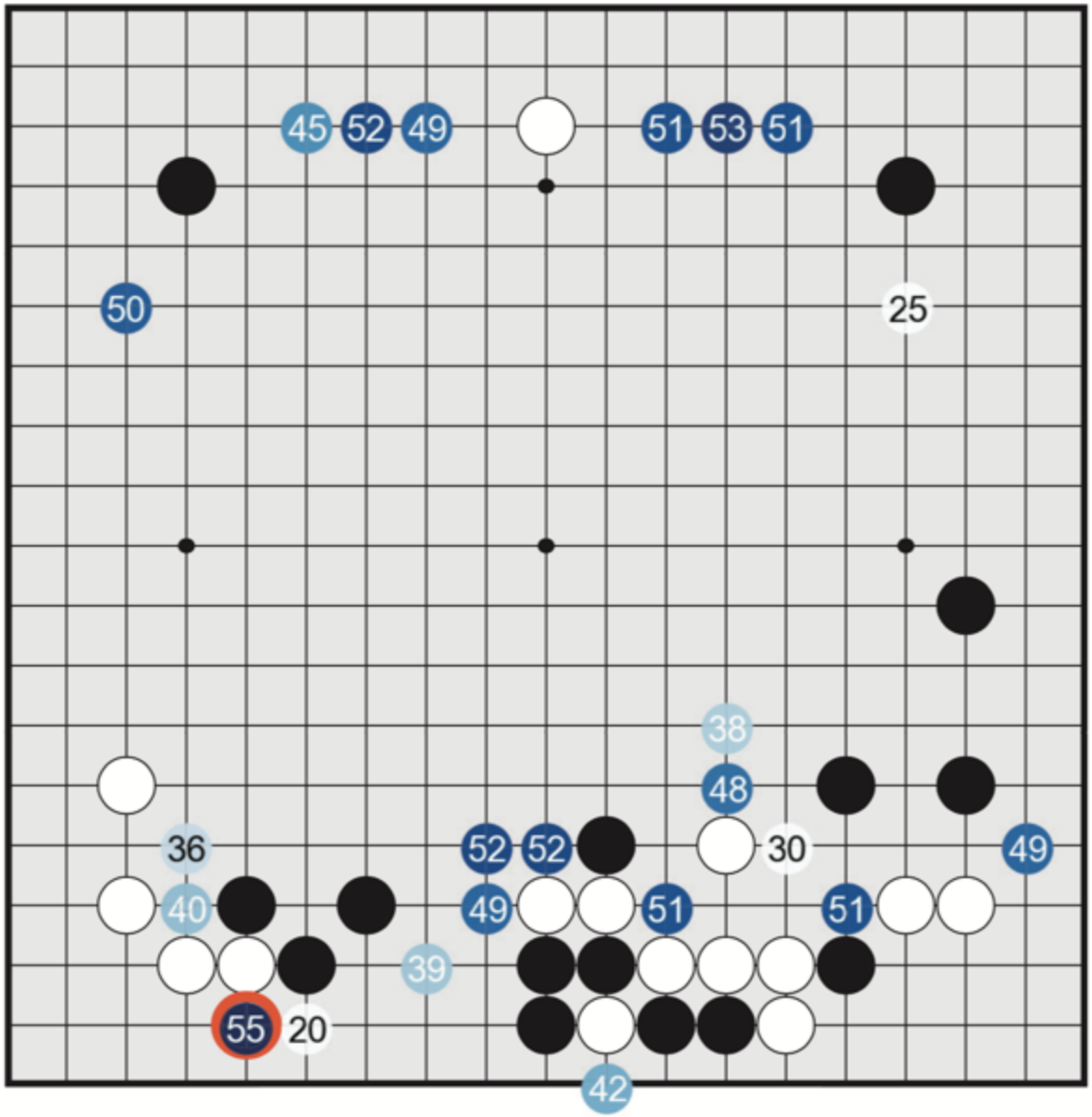
EXAMPLE OF PLAY – INFORMAL GAME AGAINST FAN HUI – VALUE NETWORK



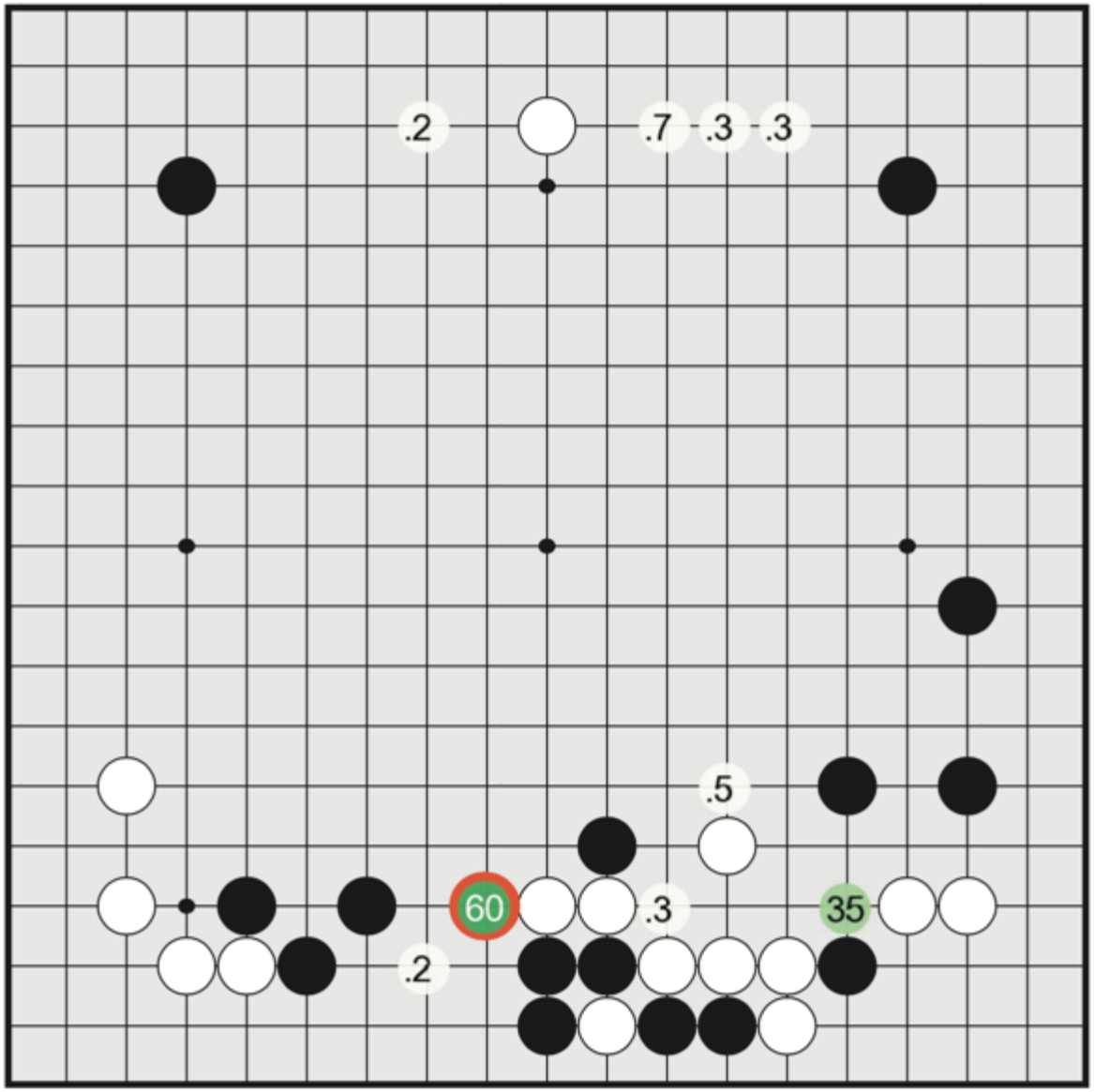
Evaluation using Tree and value NN only



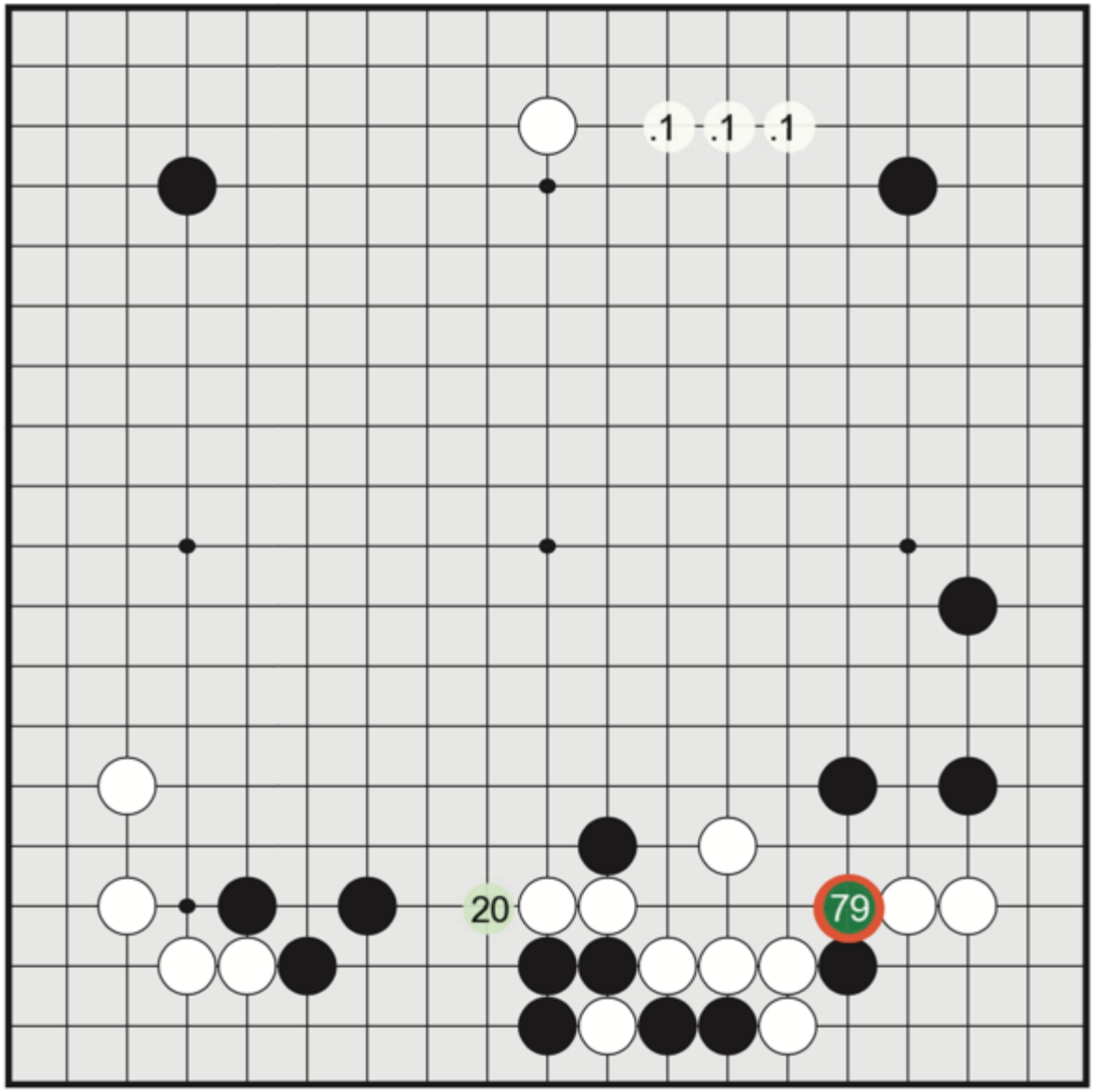
EVALUATION USING TREE AND RANDOM ROLLOUTS ONLY



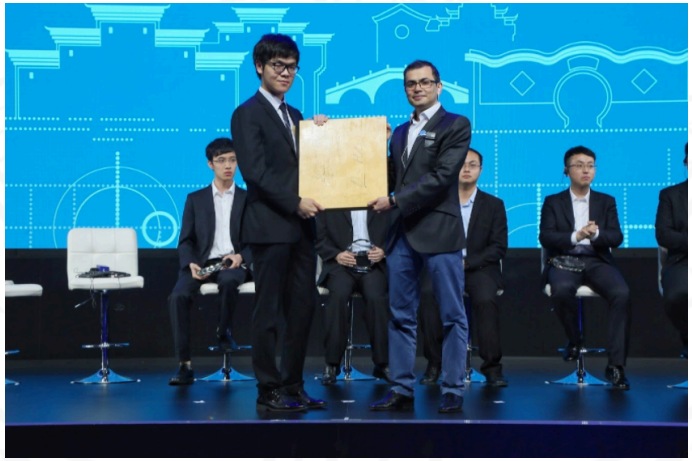
POLICY NN



NUMBER OF TIMES A MOVE WAS VISITED



"This Summit is one of the greatest matches that I've had. I believe, it's actually one of the greatest matches in history." — Ke Jie, 9 Dan Professional, during the post match wrap up



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