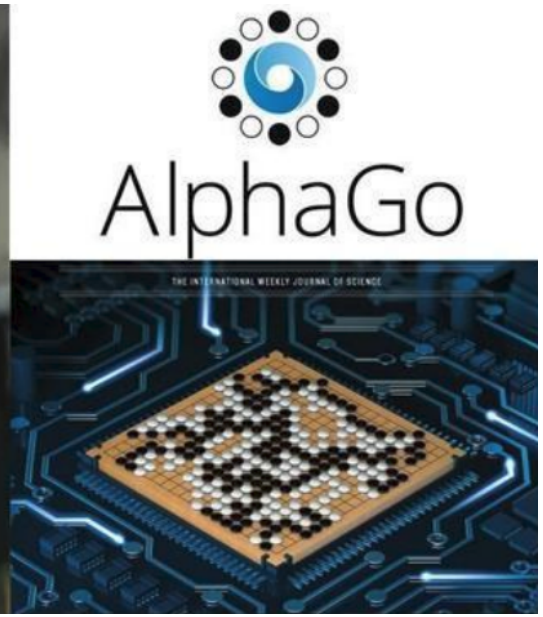
Mastering Games with Deep Learning

Tomáš Brázdil



AI in Games

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Tests human like intelligence in a controlled and measurable environment.

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Some played by AI with super-human skills: Chess

Some have been considered too hard: **Go**

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Computer games (**Starcraft**, Call of Duty, Civilization, etc.):

- AI present from their advent

  Quality of AI is crucial in assessment of computer games.
- Typically complex graphical interface and possible behavior

Learning AI

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- Developed in 90s
- Neural networks based reinforcement learning algorithm playing backgammon
- Reached expert level by self-play
- Except input-output, no part of the algorithm specific for backgammon

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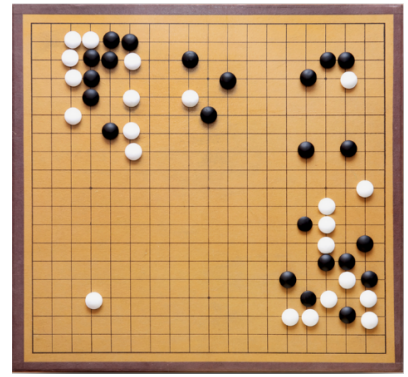
This talk:

- Self-playing learning algorithm for Go
- Starcraft 2 challenge

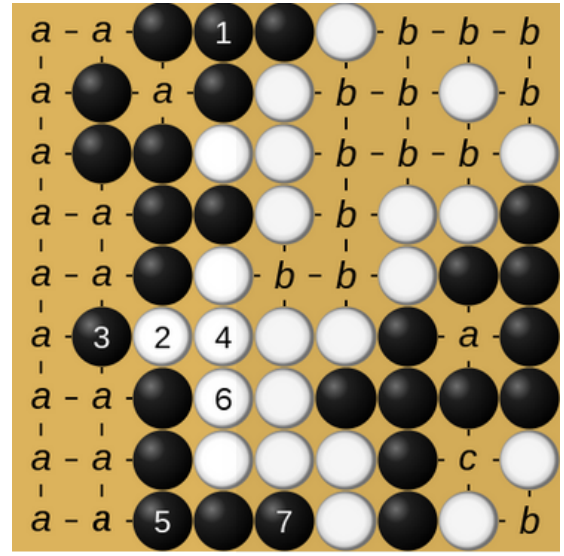
GO



Rules (roughly):

- Two players
- Take turns placing stones on the vacant intersections ("points") of a board with a 19x19 grid of lines
- Stones cannot be moved but are removed from the board when surrounded by opposing stones (captured)

- The game proceeds until neither player wishes to make another move
- The surrounded area (territory) is counted along with captured stones

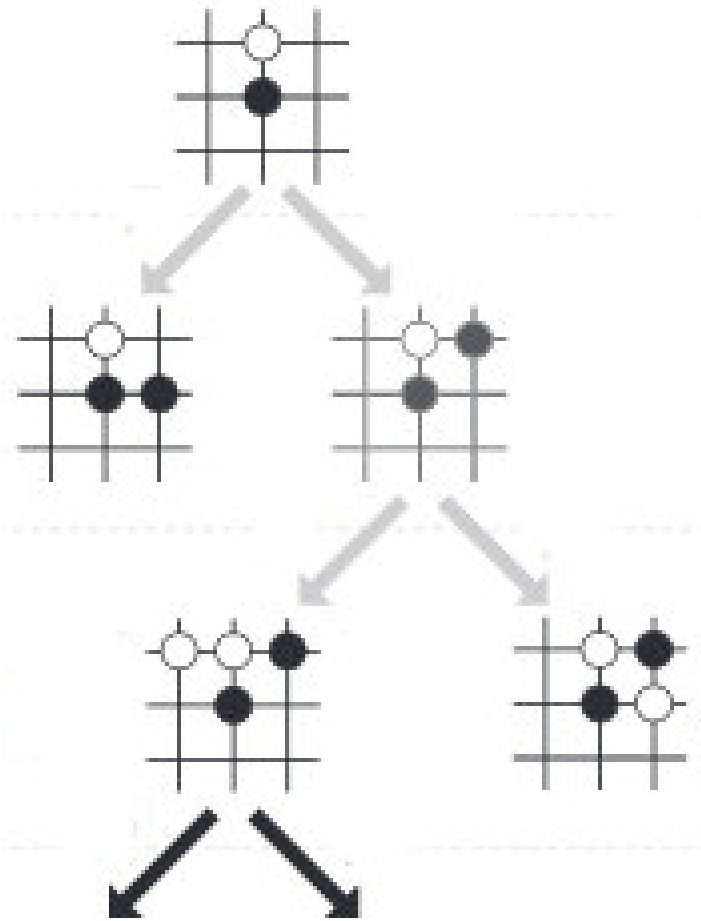


Basic notation

- States

  Each state is controlled by one of the players, **Li** and **Wang**

  GO: Current board configuration



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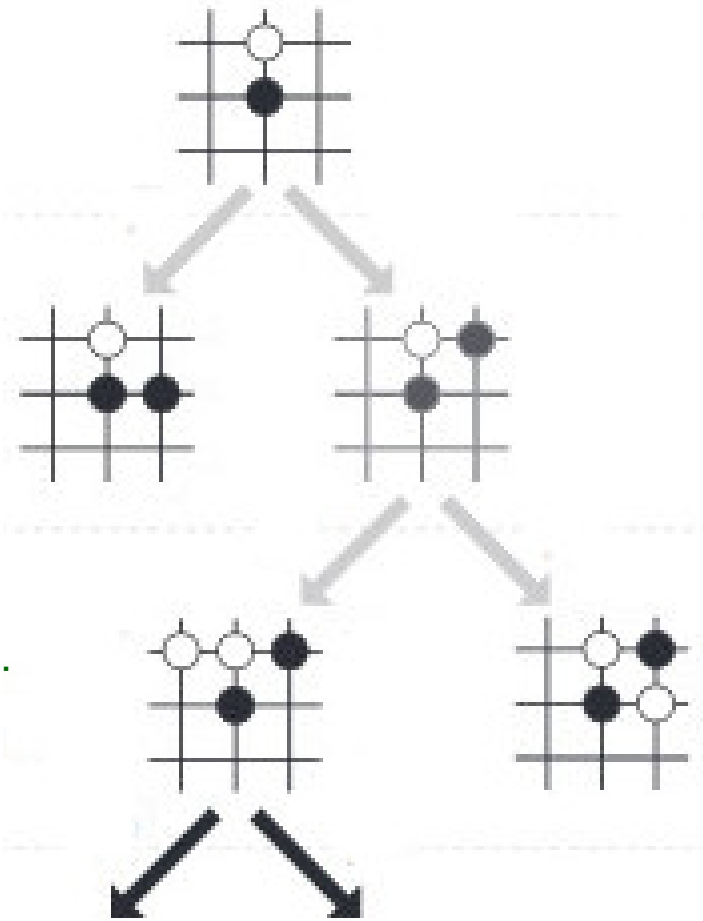

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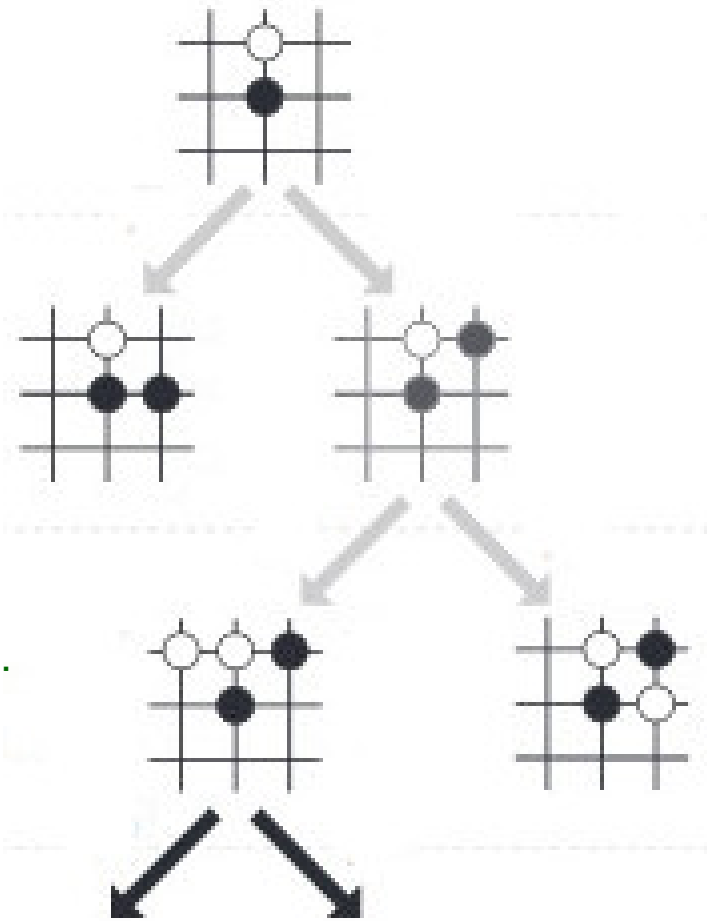

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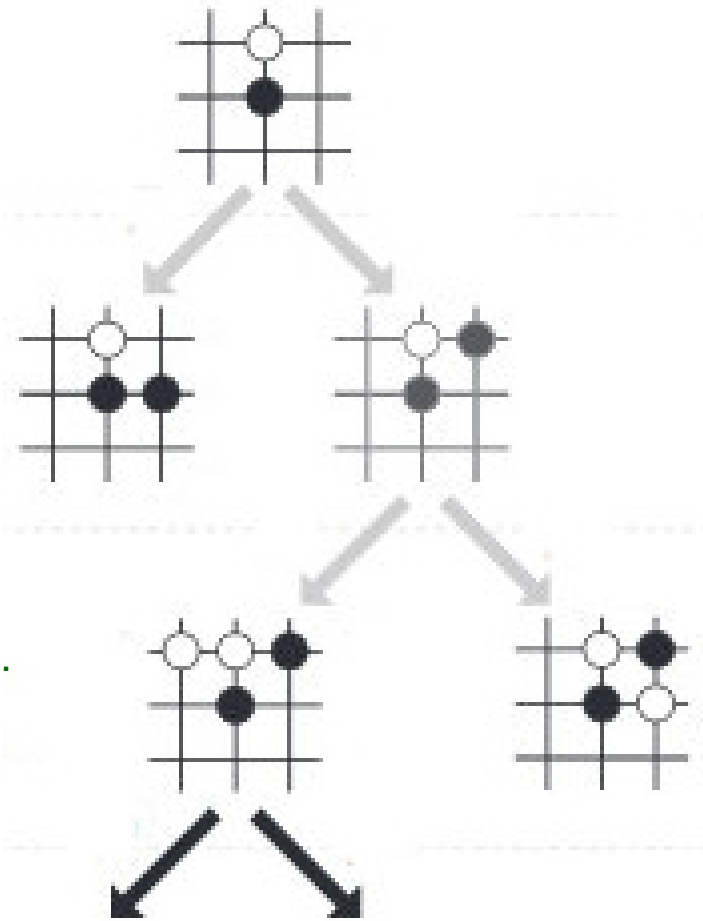

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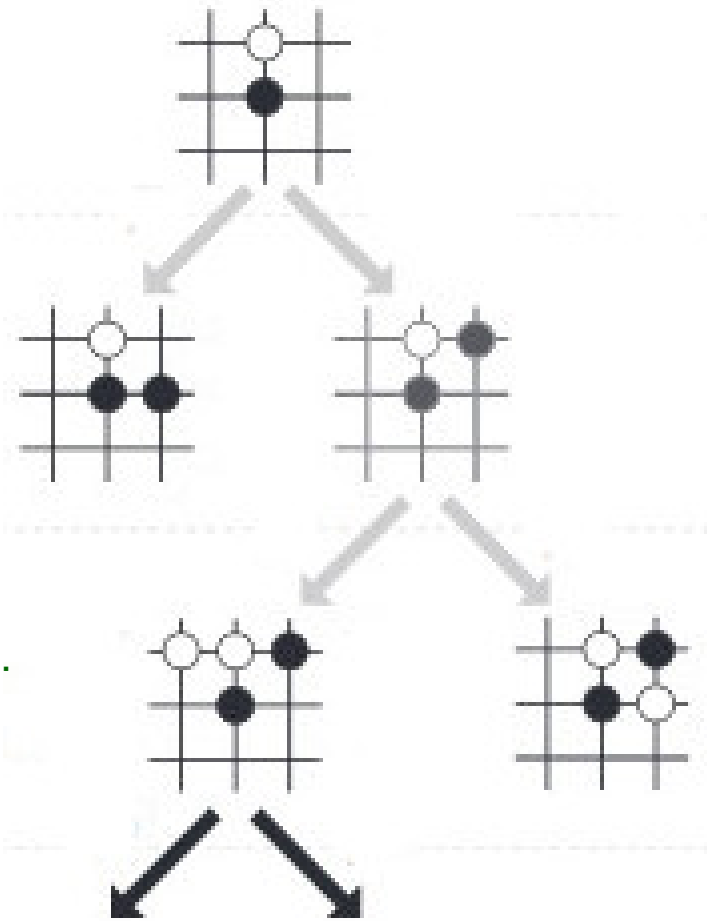

Strategy of a player is a function which to every state controlled by the player assigns an enabled action (possibly in random).

Backward induction

How to find an optimal strategy?

Evaluate possible transitions from the end to the start

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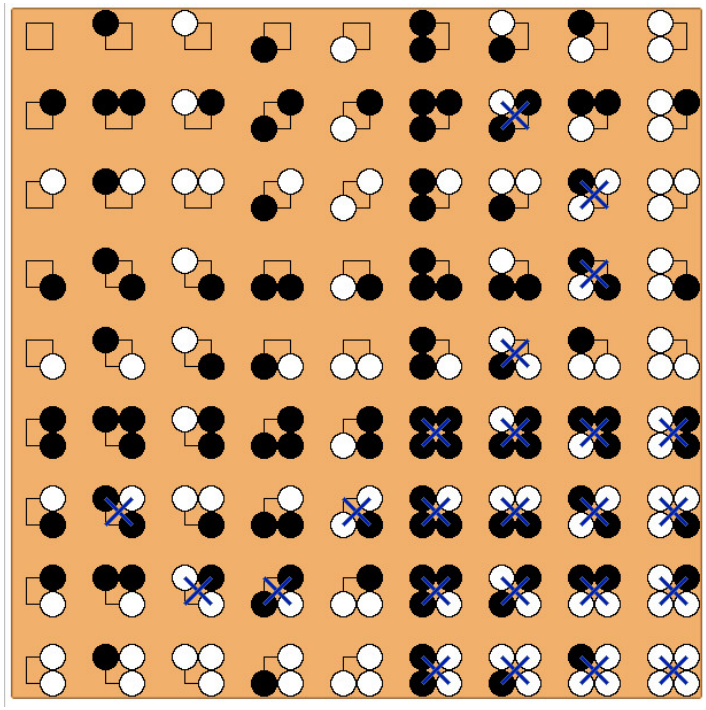
... but backward induction does not work for larger games ...

Size of GO

2x2 variant: 81 possible board positions, out of which 57 legal.



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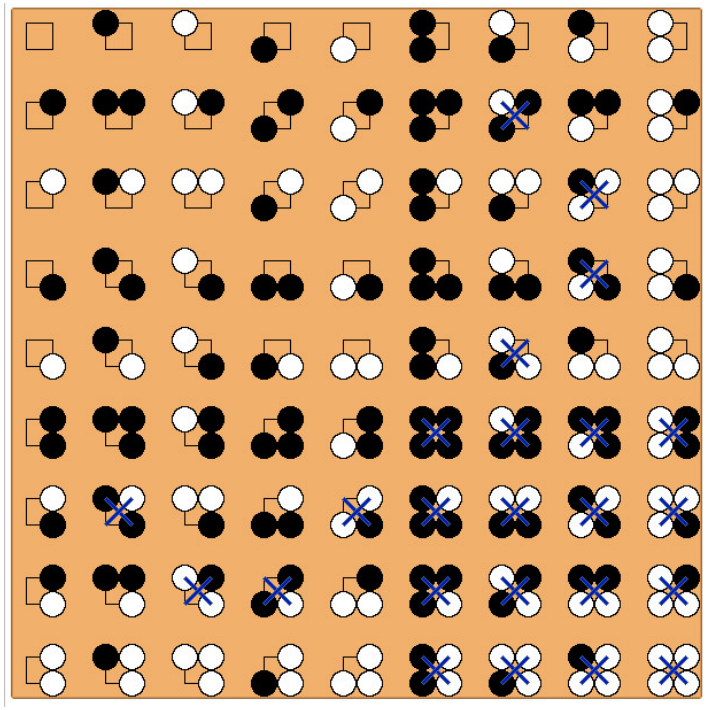

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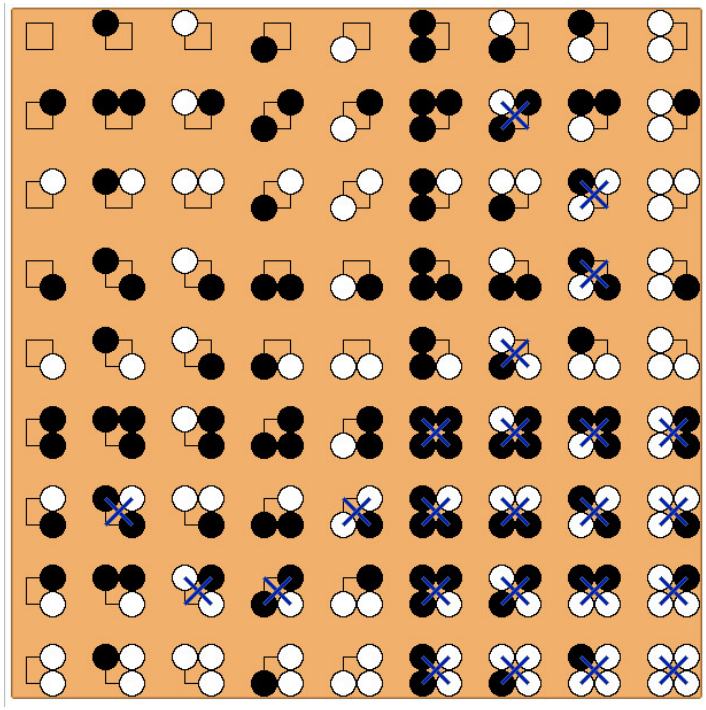

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Legal game positions: $2.08168199382 * 10^{170}$
Branching degree approx. 250

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Exhaustive search (backward induction) impossible.

Heuristic/approximate/learning solutions possible but only (strong) amateur level.

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Silver et al. Mastering the game of Go with deep neural networks and tree search. Nature 529(7587): 484-489 (2016)

achieved grand-master level using three well known concepts:

- Monte Carlo tree search

  search for best actions
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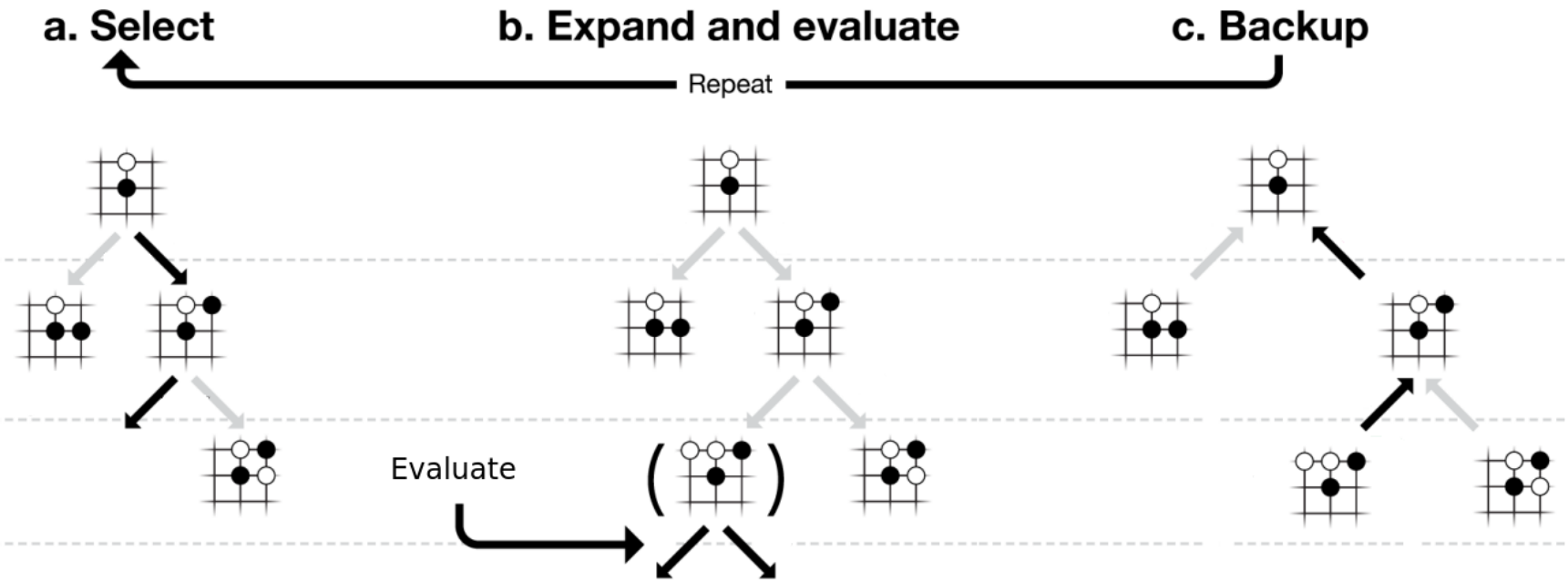

To make a decision in a particular state s_{root}

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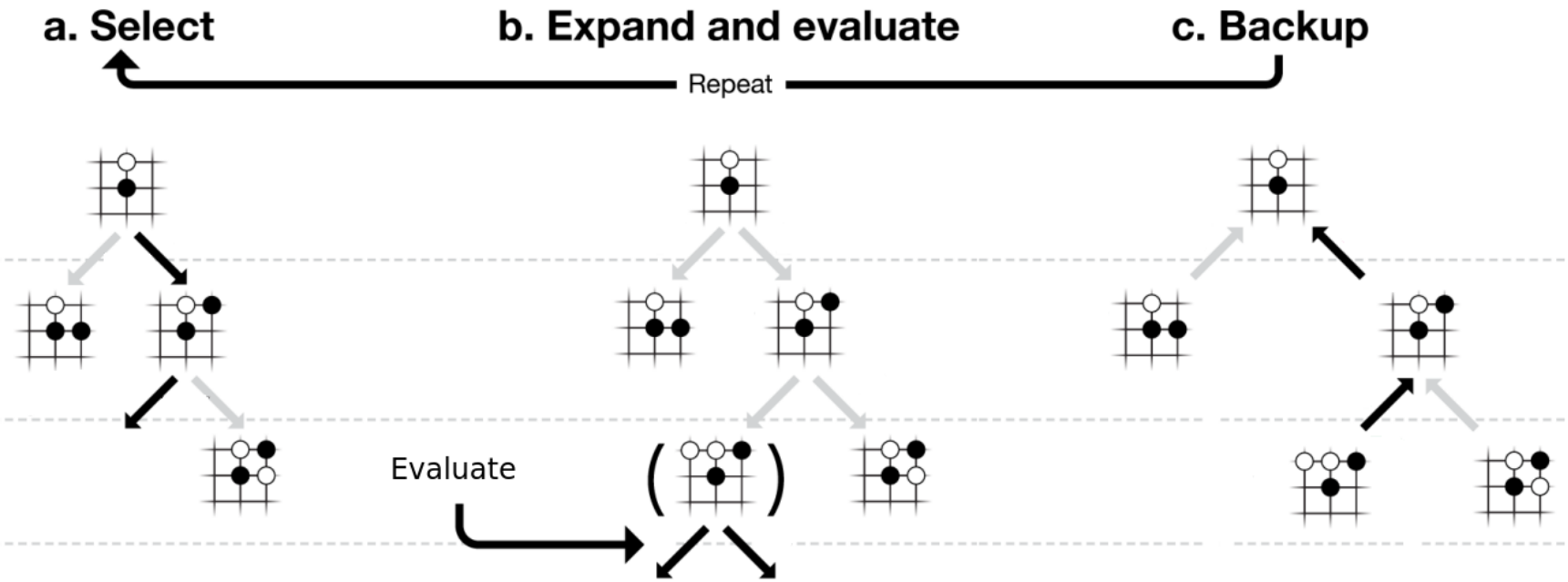

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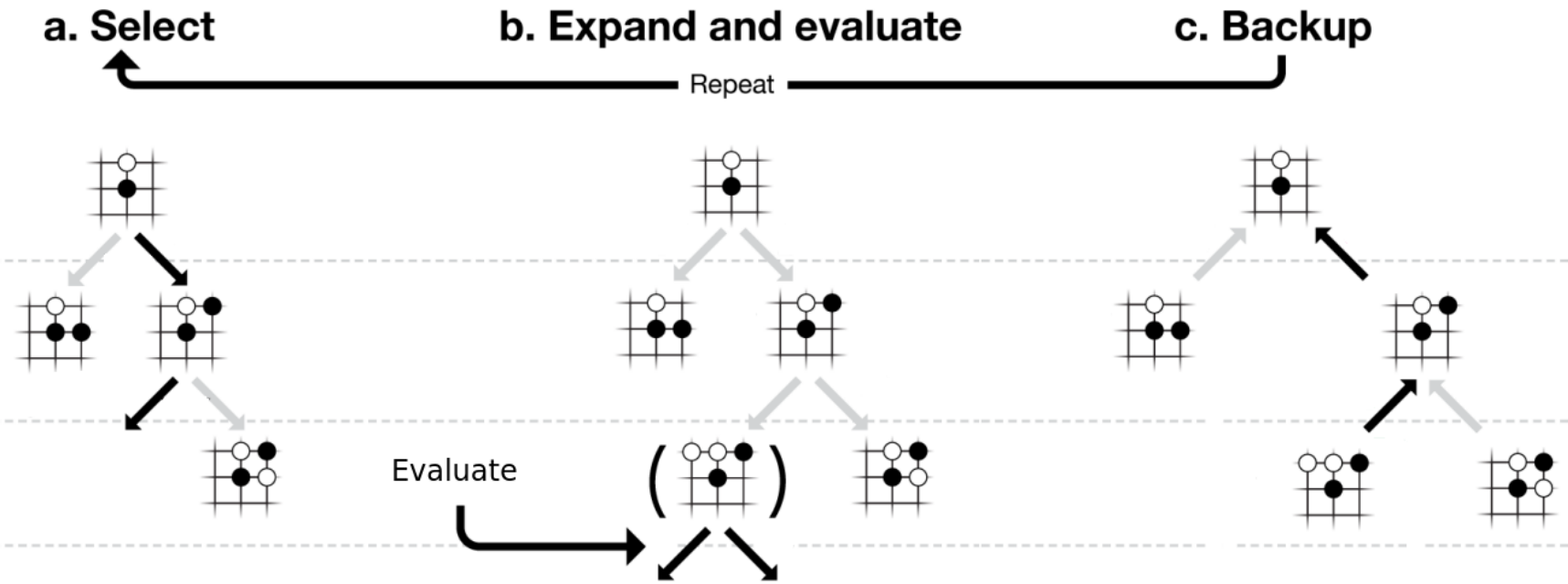

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- iteratively grow a lookahead tree rooted in s_{root}
- in every iteration
  - add a new leaf at the end of the "most promising path"
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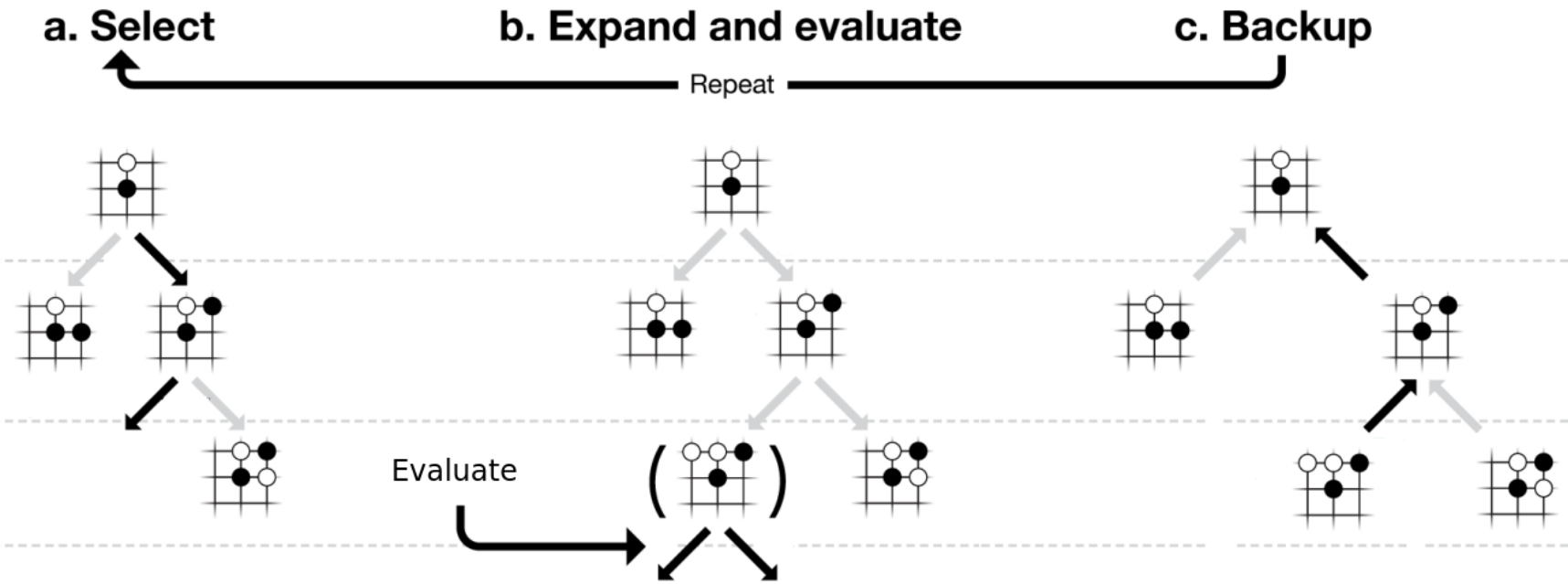

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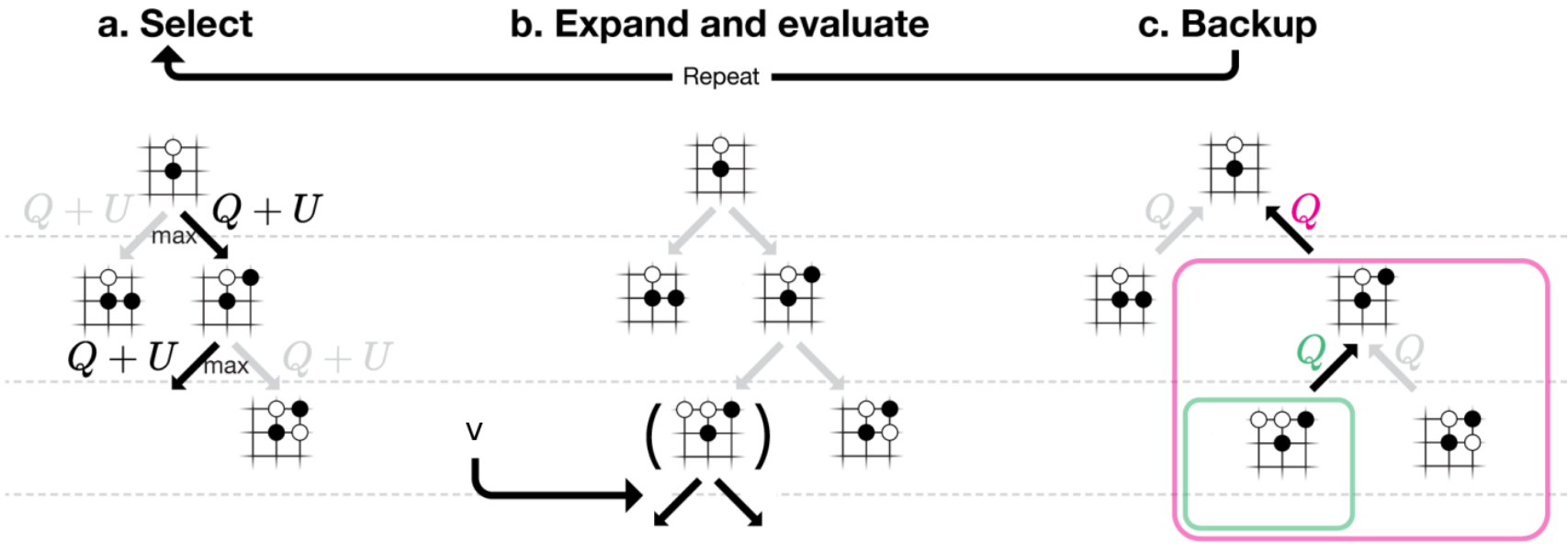
How to select the nodes? How to evaluate?

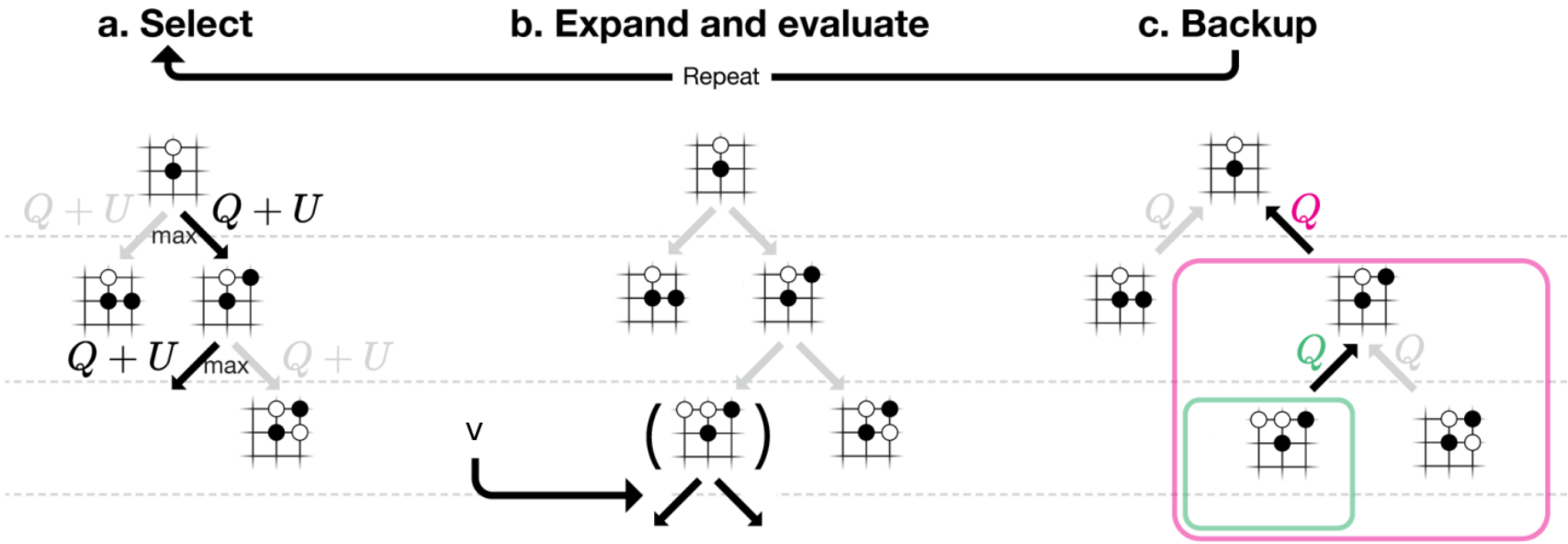


f_θ = parametrized function such that for every state s

$$(\mathbf{p}, v) = f_\theta(s)$$

- $\mathbf{p}$ = probability distribution on actions enabled in s
- v = prior value estimate for s

f_θ computed by a deep neural network, θ weights of the network



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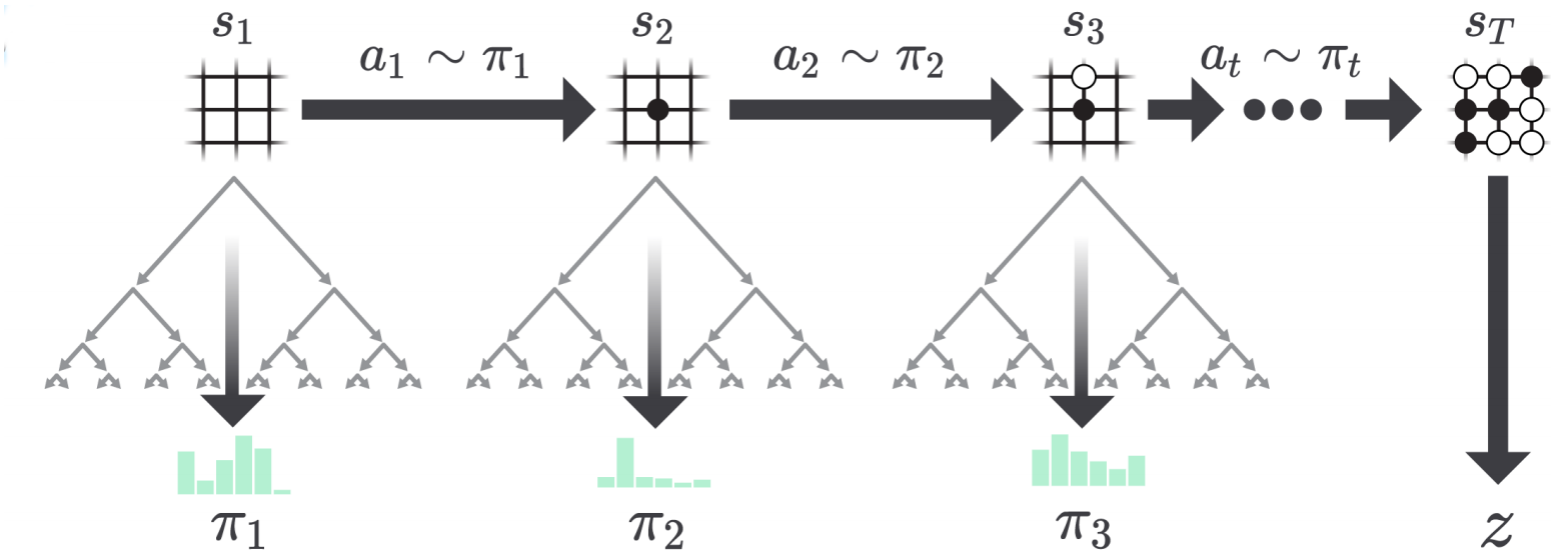
MCTS uses v to get *mean action value* Q and uses $\mathbf{p}$ to get an *upper bound* U which influences the selection.

Strategy

In every step perform the MCTS.



Action a_t enabled in state s_t is chosen with the probability

$$\pi_t(a_t) = \frac{N(s_t, a_t)^{1/\tau}}{N(s_t)} \quad \text{where} \quad N(s_t) = \sum_{a'} N(s_t, a')^{1/\tau}$$

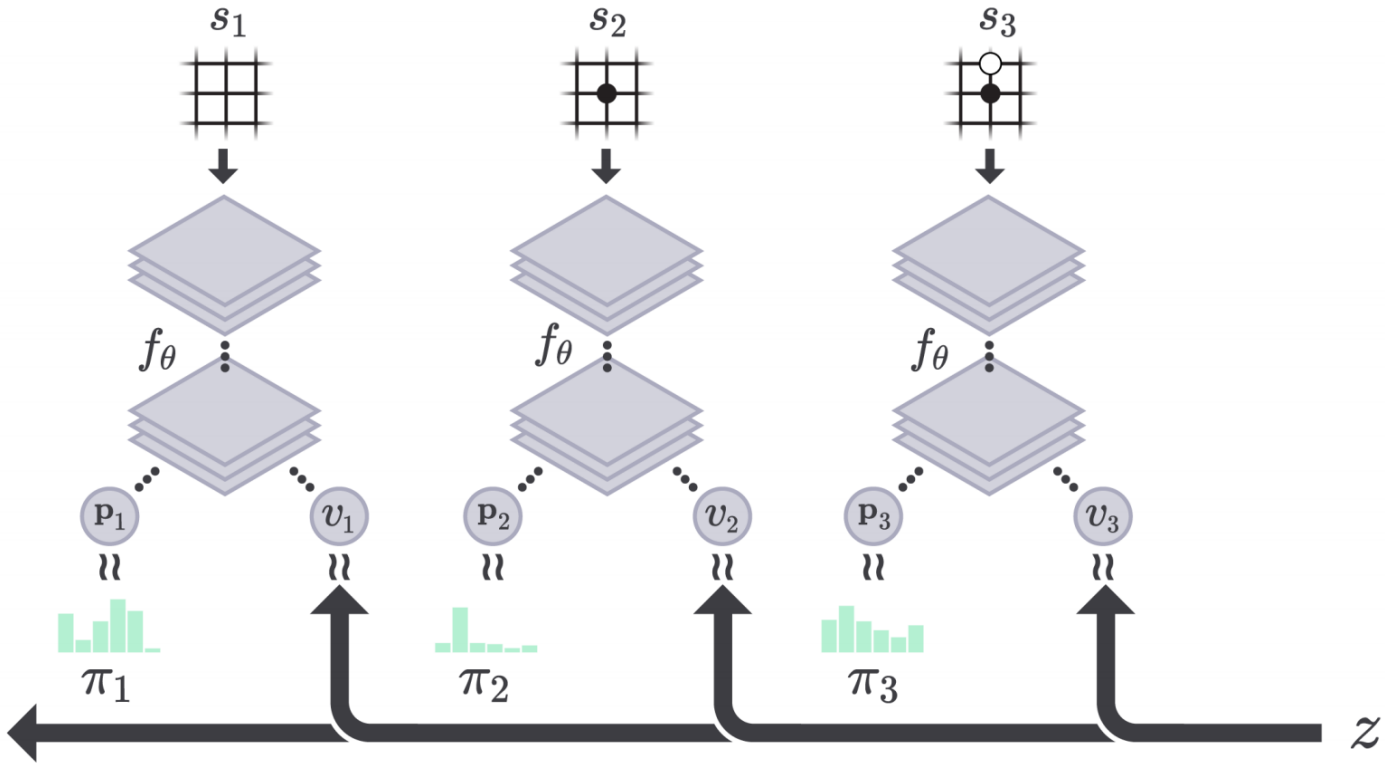
$N(s_t, a_t)$ = the number of times MCTS rooted in s_t takes the transition (s_t, a_t).

$\tau \to 0 \approx$ maximum probability action

Training

f_θ is trained in self-play reinforcement learning using MCTS.

Play according to f_θ using MCTS till the end of the game.



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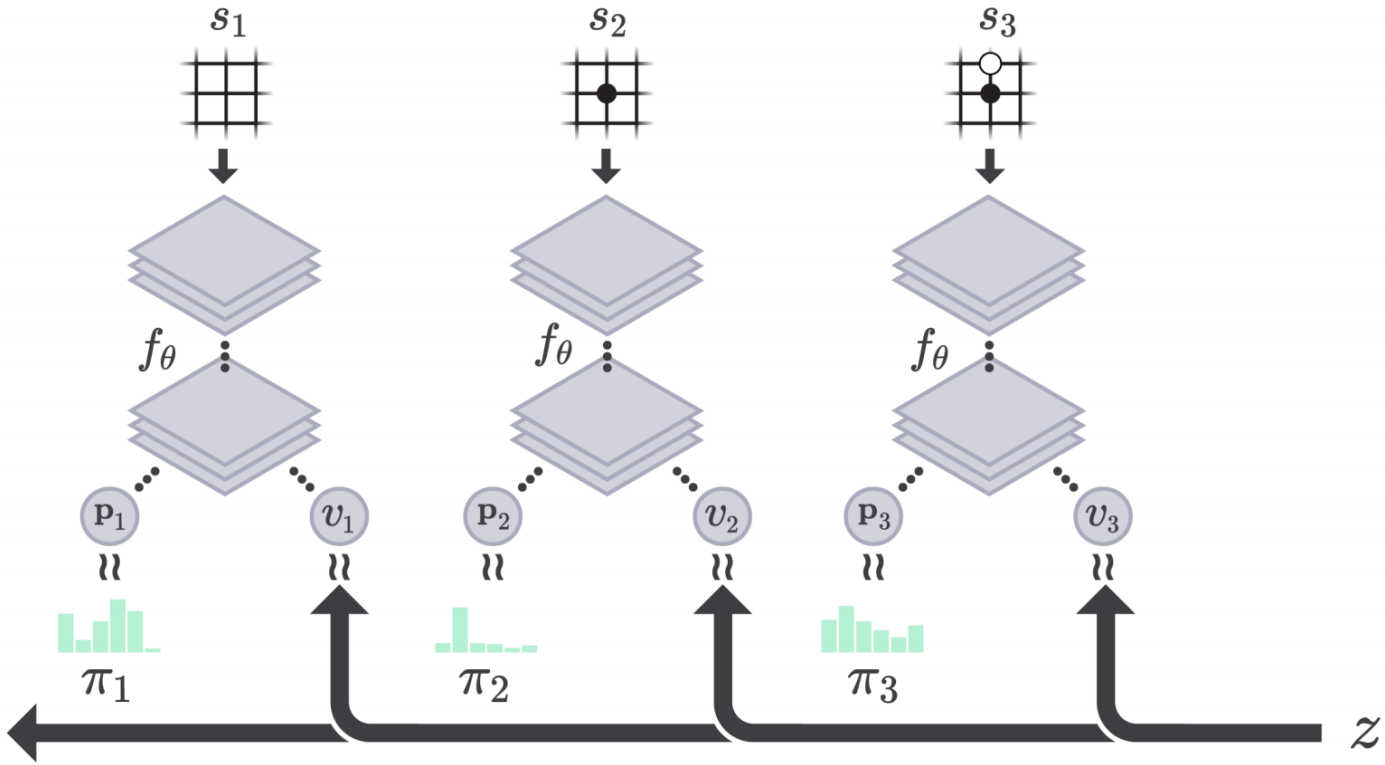
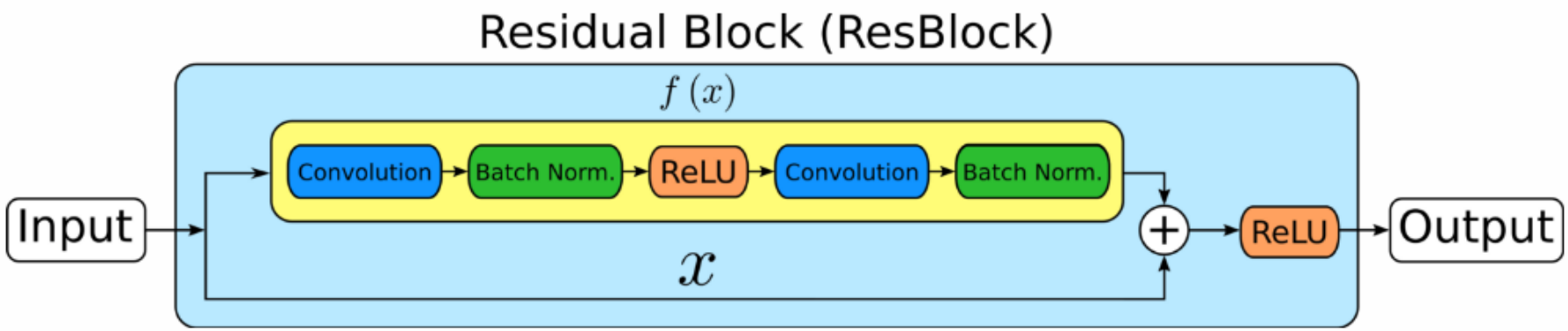


Adjust θ so that for $(\mathbf{p}_t, v_t) = f_\theta(s_t)$

- $\mathbf{p}_t$ gets closer to π_t
- v_t gets closer to the true result z of the game

  $z = \pm 1$ from the point of view of the owner of s_t

Network & Training



Network f_θ = 1 convolutional followed by 39 residual blocks

Input: 8 last raw board configurations

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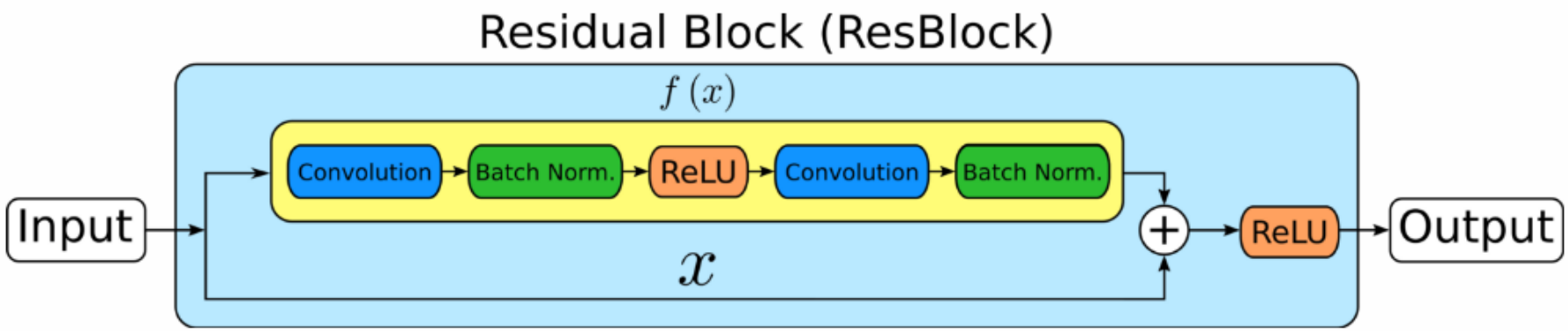

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Training:

- Randomly initialized
- 4.9 million games of self-play
- 1,600 simulations for each MCTS, approximately 0.4s thinking time per move

Comparison

	AlphaGo Zero (new version)	AlphaGo Lee (older version)
Prior info	None, initialized randomly	database of human plays
Network	1 conv. (256 filters each) + 39 residual	12 conv. (256 filters each)
Training HW	64 GPU + 19 CPU	50 GPU
Training	36 hours	month
Playing HW	one machine, 4 TPUs	many machines, 48 TPUs
Defeated	AlphaGo Lee, 100:0	best players in the world, best computer programs: Crazy Stone, Zen, Pachi and Fuego

AlphaGo in action

AlphaGo Lee (older version) defeated Lee Sedol

9. dan, ranked second in international titles

- Chinese rules with a 7.5-point komi

  7.5 points added to the score of the white player for playing second
- Two-hour set time limit for each player followed by three 60-second byo-yomi overtime periods
- AlphaGo Lee won four games, Lee Sedol one

Lee apologized for his losses, stating after game three that he misjudged the capabilities of AlphaGo and felt powerless.

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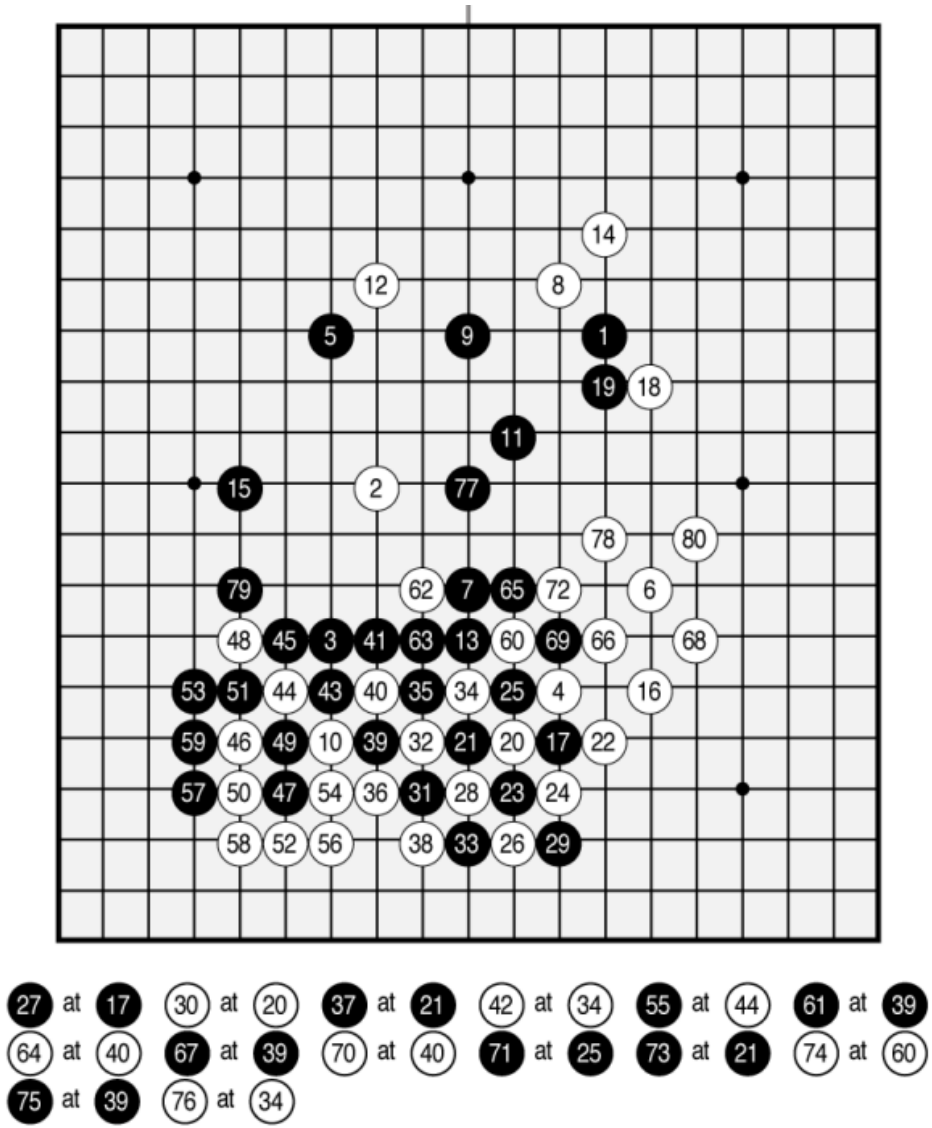
Alpha Go Zero (new version) won 100 out of 100 games against **AlphaGo Lee** (older version) under the conditions of the match with Lee Sedol.

Learning behavior

After 3 hours of learning:



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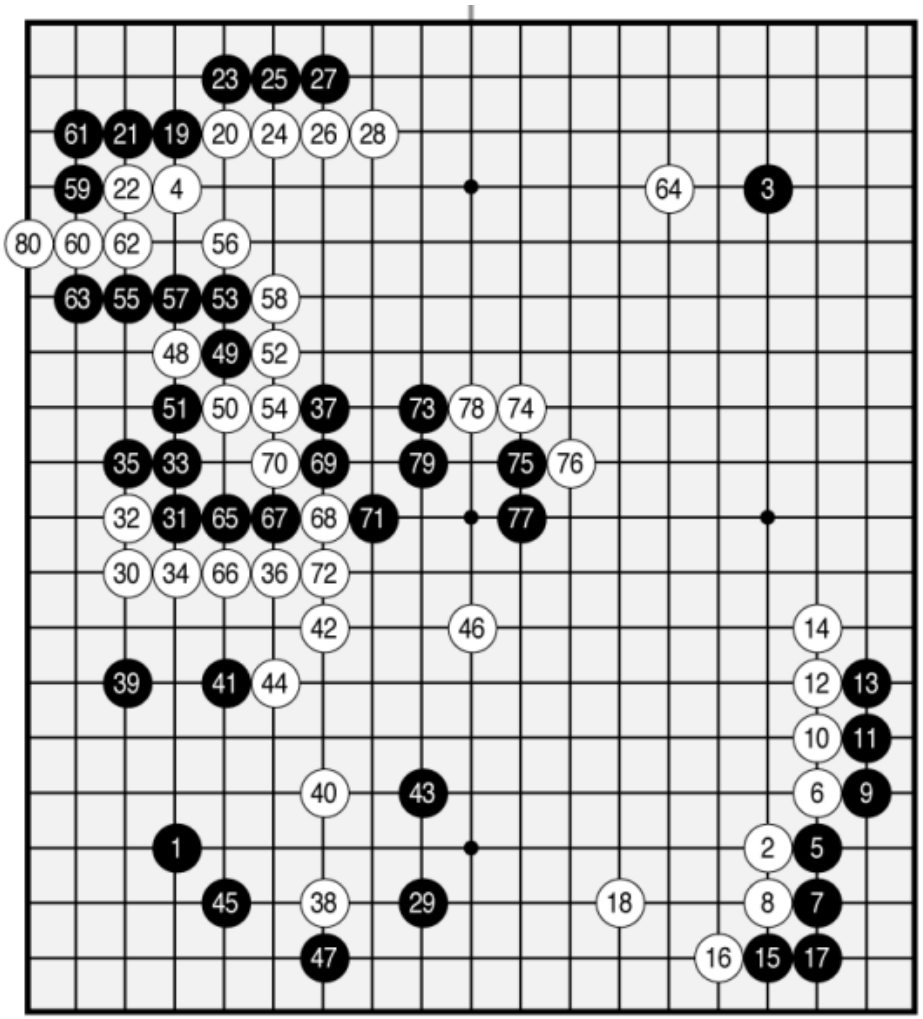
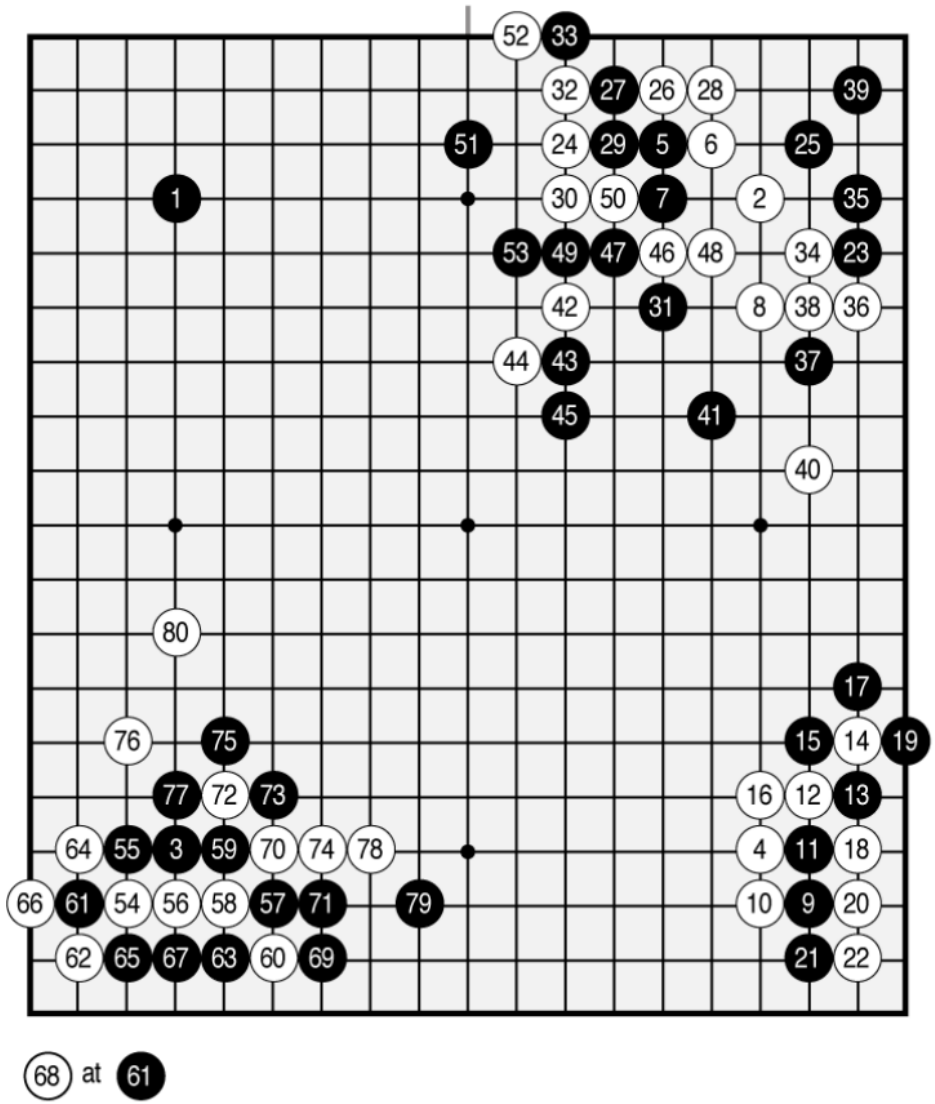
After 19 hours of learning:



Learning behavior

After 70 hours of learning:



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Brázdil:
"Don't Panic! AI still sucks in real-world strategic reasoning."

Starcraft 2

Real-time strategic game produced by Blizzard Entertainment.

Played by milions of people, tournaments, etc.

Starcraft 2 - principles & challenges

To win a game players must:

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- Construct production buildings
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- Huge action space (GUI, many "moving parts"): Approx. 10^8

So far, learning AI solves only trivial minigames.

Starcraft 2 Learning Environment

- Machine Learning API developed by Blizzard (even for Linux).
- Dataset of 65,000 anonymised game replays

  promised to grow to millions soon
- Open source version of DeepMind's toolset PySC2
  - Simplified interface for RL agents to interact with StarCraft 2, getting observations and sending actions
  - Simple minigames to test basic AI

Results on full game

- Agents trained with sparse ternary rewards managed to avoid constant losses by using the Terran ability to lift and then move buildings out of attack range
- Agents trained with the Blizzard score converged to trivial strategies that simply preserved the initial mining process without building further units or structures

Conclusions

I have shown you

- super-human AI,

  ... playing Go
- trained by self-play, i.e. completely on its own,
- using amazingly simple algorithms,
- and relatively cheap hardware.

I have also shown you current limits of such AI

... it fails miserably in Starcraft 2