Monte-Carlo Game Tree Search, Machine Learning and Deep Learning

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Abstract

- **Combining domain dependent knowledge obtained using machine learning and deep learning techniques.**
  - **Node expansion**
  - **Better simulation policy**
  - **Better position evaluation**
- **Conclusion:**
  - **Combining the power of machine learning and deep learning, Monte-Carlo approach is now above human players for computer Go.**

Domain dependent refinements

- **Main technique:**
  - **Adding domain knowledge.**
- **We use computer Go as an example here.**
- **Refinements come from machine learning and/or deep learning via training and prediction.**
  - **During the expansion phase:**
    - ▷ *Special case: open game.*
    - ▷ *General case: use domain knowledge to expand only the nodes that are meaningful with respect to the game considered, e.g., Go.*
  - **During the simulation phase: try to find a better simulation policy.**
    - ▷ *Simulation balancing for getting a better playout policy.*
    - ▷ *Other techniques are also known.*
- **Prediction of board evaluations, not just good moves.**
  - ▷ *Combined with UCB score to form a better estimation on how good or bad the current position is.*
  - ▷ *To start a simulation with a good prior knowledge.*
  - ▷ *To end a simulation earlier when something very bad or very good has already happened.*

Warnings

- **We only tell you how machine/deep learning are used in game playing by expecting the audience having some prior knowledge.**
- **We do not cover machine/deep learning theory, tool or implementation in this course.**

How domain knowledge can be obtained

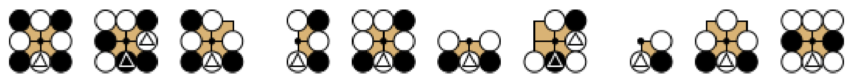
- Via human experts: very expensive to get and very difficult to be complete as proven by studies before year 2004 such as GNU Go.
- Machine learning.
  - (Local) pattern: treat positions as pictures and find important patterns and shapes within them.
    - *K by K sub-boards such as $K = 3$.*
    - *Diamond shaped patterns with different widths.*
    - *...*
  - (Global) feature: find semantics of positions.
    - *The liberties of each stone.*
    - *The number of stones can be captured by playing this intersection.*
    - *...*
  - Advanced knowledge: (higher ordered) information such as history dependent ones, namely cannot be captured using only the current position.
    - *Ko.*
    - *Features include previous several plys of a position.*
    - *A ply that has an effect to be realized a long turns latter.*

3 by 3 patterns

- **[Huang et al'10]**

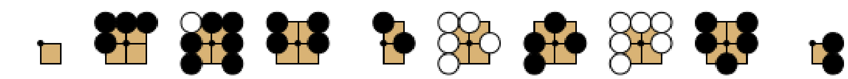
Table 4. 3×3 patterns. A triangle indicates a stone in atari. Black to move.

SB rank	1	2	3	4	5	6	7	8	9	10
MM rank	816	1029	8	1058	1055	403	441	431	960	555
SB γ	47.63	30.85	29.33	29.26	25.53	25.51	25.24	15.72	15.03	14.64
MM γ	1.55	0.95	16.98	0.88	0.89	3.34	3.10	3.15	1.10	2.50

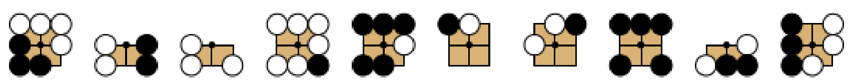


SB rank	1371	951	1870	1519	1941	148	546	3	1486	1180
MM rank	1	2	3	4	5	6	7	8	9	10
SB γ	0.92	1.01	0.43	0.85	0.24	2.35	1.13	29.33	0.86	0.98
MM γ	112.30	52.78	45.68	39.43	30.41	25.52	24.16	16.98	14.66	14.34

SB rank	2008	2007	2006	2005	2004	2003	2002	2001	2000	1999
MM rank	1982	1573	1734	2008	1762	1953	1907	1999	1971	1751
SB γ	0.02	0.02	0.03	0.03	0.04	0.04	0.04	0.04	0.05	0.06
MM γ	0.00	0.21	0.08	0.00	0.07	0.01	0.01	0.00	0.00	0.07



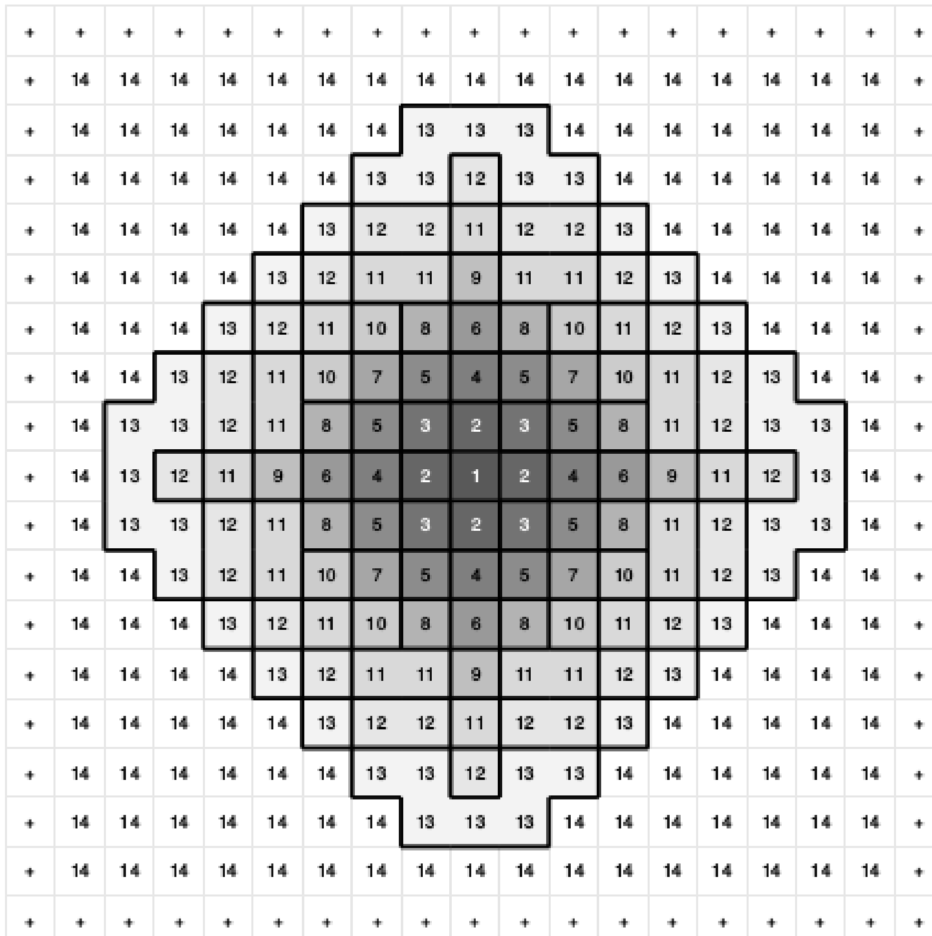
SB rank	2005	1896	1929	251	1910	1818	1874	1969	1915	2001
MM rank	2008	2007	2006	2005	2004	2003	2002	2001	2000	1999
SB γ	0.03	0.36	0.28	1.60	0.34	0.53	0.42	0.16	0.33	0.04
MM γ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00



SB rank	11	13	14	15	16	19	25	27	28	32
MM rank	1847	1770	1775	1808	1509	420	900	1857	425	1482
SB γ	14.43	14.15	12.36	12.33	11.71	9.82	8.23	8.11	7.93	7.29
MM γ	0.03	0.07	0.06	0.04	0.28	3.25	1.27	0.03	3.21	0.29

Diamond shaped patterns

- **[Stern et al'06]**



Supervised learning

- **Use supervised learning to get a good prediction on the move to choose when a position is given: a vast amount of expert games with possible annotations are available.**
  - **Training phase.**
    - ▷ *Feed positions and their corresponding actions (moves) in expert games into the learning program.*
    - ▷ *Feature and pattern extraction from these positions.*
  - **Prediction phase.**
    - ▷ *Predict the probability of a move will be taken when a position is encountered.*
- **Many different paradigms and algorithms.**
  - **A very active research area with many applications.**

Reinforcement learning

- Use reinforcement learning to boost the baseline prediction, obtained from supervised learning for example, using self-play or expert annotated games.
  - The baseline one needs to be good enough to achieve some visible improvement.
  - Feed evaluations of positions from the baseline one into the learning program.
    - ▷ *The objective of the learning is different from the supervised learning phase.*
    - ▷ *To learn which move will result in better positions, namely positions with better evaluations.*
- Note that the predictions of moves best matched with the training data, and moves best matched with better positions may be very different.
- Many different paradigms and algorithms.
  - Another very active research area with many applications.
  - Some claimed that no baseline obtained from supervised learning is needed if the rate of convergence is fast enough [Silver et al 2017].

History

- **Using machine learning to aid computer Go programs is not new.**
  - **NeuroGo [Enzenberger'96]: neural network based move predication.**
  - **IndiGo [Bouzy and Chaslot'05]: Bayesian network.**
- **Pure learning approach is very difficult to compete with top computer Go programs with searching before AlphaGo.**
  - **Need to combine some forms of searching.**
- **Computing constraints.**
  - **It is costly, or resource consuming, to do deep learning.**
  - **In 2017, DeepMind team claimed that no supervised learning is needed even the training time is limited in training AlphaGo Zero [Silver et al 2017].**

Combining with MCTS

- **Places that MCTS needs helps.**
  - **The expansion phase: what children to explore when a leaf is to be expanded.**
  - **The simulation phase.**
    - ▷ *Originally almost random games are generated: needs a huge amount of simulated games to have a high confidence in the outcome.*
    - ▷ *Can we use more domain knowledge to get a better confidence using the same number of simulations?*
  - **Position evaluation: to end a simulation earlier or to start a simulation with better prior knowledge.**
- **Fundamental issue: assume we can only afford to use a fixed amount of resources R, say computing power in a given time constraint.**
  - **Assume each simulation takes r_s amount of resources for a strategy s in generating a playout.**
    - ▷ *Hence we can only afford to have $\lfloor \frac{R}{r_s} \rfloor$ playouts.*
  - **How to pick s to maximize c_s, the confidence or quality?**
    - ▷ *Difficult to define confidence or quality.*
  - **Not likely that r_s is linearly proportional to c_s.**

Machine learning

- **Many different framework and theories.**
  - **Decision tree.**
  - **Support vector machine.**
  - **Bayesian network.**
  - **Artificial neural network (ANN).**
  - ...
- **Here we will only introduce Bayesian network and multi-layer artificial neural network which includes convolutional neural network (CNN) and deep neural network (DNN).**
- **For each framework, depending on how the underlying optimization problem is solved, there are many different simplified models.**
  - **We will only introduce some popular models used in game playing.**
  - **There are many open-source or public domain software available.**

Bayesian network based learning (1/3)

- **Bayes theorem:** $P(B \mid A) = \frac{P(A|B)P(B)}{P(A)}$.
  - A: features and patterns
  - B: an action or a move
  - $P(A)$: probability of A happens in the training data set
  - $P(B)$: probability of an action B is taken
  - $P(A \mid B)$: probability of A appears in the training set when an action B is taken.
    - ▷ *This is the training phase.*
    - ▷ *We can compute this information from historical records.*
  - $P(B \mid A)$: when A appears, the prediction of B is taken.
    - ▷ *This is what we want.*
- **Assume there are two actions B_1 and B_2 that one can take in a position with the feature set A, then one uses the values of $P(B_1 \mid A)$ and $P(B_2 \mid A)$ to make a decision.**
  - Take one with a larger value.
  - Take one with a chance proportional to its value.
  - Take one with a chance using the idea of simulating annealing.
  - $\cdots$

Bayesian network based learning (2/3)

- **When the training set is huge and the feature set A is large, it is very time and space consuming to compute everything exactly.**
  - **In many cases, exact computation is impossible.**
    - ***Training data are usually huge in quantity, may contain error, and most of the time incomplete.***
    - ***When there are many features in a position, it is very time and space consuming to compute $P(B \mid A)$.***
- **Use some sort of approximation.**
  - **Assume a position P is consisted of features $\mathcal{P} = \{P_{A_1}, P_{A_2}, \ldots, P_{A_w}\}$.**
  - **For a possible child position B of P, give each feature P_{A_i} a strength or influence parameter $q(B, P_{A_i})$ so that it approximates the probability of $P(B \mid P_{A_i})$.**
  - **Use a function $f(q(B, P_{A_1}), \ldots, q(B, P_{A_w}))$ to approximate the value of $P(B \mid \mathcal{P})$.**

Bayesian network based learning (3/3)

- **Many different models exist to approximate the strength or influence parameter, θ, of a party, player, feature or pattern.**
  - **Bradley-Terry (BT) model.**
    - ▷ *Given 2 players with strengths θ_i and θ_j, $P(i \text{ beats } j) = \frac{e^{\theta_i}}{e^{\theta_i}+e^{\theta_j}}$.*
    - ▷ *Generalized model: Comparisons between teams of players, say odds of players $i+j$ beats both $k+m$ and $j+n+p$ is $\frac{e^{\theta_i+\theta_j}}{e^{\theta_i+\theta_j}+e^{\theta_k+\theta_m}+e^{\theta_j+\theta_n+\theta_p}}$.*
  - **Thurstone-Mosteller (TM) model.**
    - ▷ *Given 2 players with strengths that are Gaussian distributed (or normal distributed) with $\mathcal{N}(\theta_i, \sigma_i^2)$ and $\mathcal{N}(\theta_j, \sigma_j^2)$, $P(i \text{ beats } j) = \Phi(\frac{e^{\theta_i}-e^{\theta_j}}{\sqrt{\sigma_i^2+\sigma_j^2}})$, where $\mathcal{N}(\mu, \sigma^2)$ is a normal distribution with mean μ and variance σ^2, and Φ is the c.d.f. of the standard normal distribution, namely $\mathcal{N}(0, 1)$.*
    - ▷ *Generalized TM model is more involved.*
- **May not be reasonable in real life.**
  - **Does not allow cyclic relations among players.**
  - **Strength of a team needs not to be product of teammate's strength.**
- **We will use mainly BT model to illustrate the ideas here.**

BT model in computing Elo

- **This is also how Elo rating system is computed between players in games like Chess or Go.**
  - **Example: The Elo rating number of player i with strength θ_i is $400\log_{10}(\theta_i)$.**
    - *Assume the Elo ratings of players A, B and C are 2,800, 2,900 and 3,000 respectively.*
    - $P(C \textit{ beats } B) = \frac{10^{3000/400}}{10^{3000/400}+10^{2900/400}} = \frac{10^{7.5}}{10^{7.5}+10^{7.25}} \sim 0.64.$
    - $P(B \textit{ beats } A) = \frac{10^{2900/400}}{10^{2900/400}+10^{2800/400}} = \frac{10^{7.25}}{10^{7.25}+10^{7}} \sim 0.64.$
    - $P(C \textit{ beats } A) = \frac{10^{3000/400}}{10^{3000/400}+10^{2800/400}} = \frac{10^{7.5}}{10^{7.5}+10^{7}} \sim 0.76.$
    - *Note that $P(i \textit{ beats } j) + P(j \textit{ beats } i) = 1$ by assuming no draw.*
  - **Note: In Elo system, we use $10^{\theta_i/400}$ not e^{θ_i}.**
- **Fundamental problem:**
  - **When you have a huge set of data, how to compute the strength parameters using limited amount of resources?**
  - **The problem is even bigger when data may contain some errors and/or incomplete.**

Minorization-Maximization (MM)

- **Minorization-Maximization (MM): an approximation algorithm for the BT model [Coulom'07].**
  - Patterns: all possible, for example $3*3$ patterns, i.e., $3^9 = 19,683$ of them [Huang et al'11].
  - Training set: records of expert games.
- **During the simulation phase, use the prediction algorithm to form a random playout by finding average next moves.**
  - It is easy to have an efficient implementation.
  - Can add some amount of randomness in selecting the moves, such as using the idea of temperature in simulated annealing.
- **Results are very good: 37.86% correctness rate using 10,000 expert games [Wistuba et al'12]**
  - A very good playout policy may not be good enough for the purpose of finding out the average behavior.
    - ▷ *The samplings must consider the average "real" behavior of a player can make.*
    - ▷ *It is extremely unlikely that a player will make trivially bad moves.*
  - Need to balance the amount of resources used in carrying out the policy found and the total number of simulations can be computed.

Simulation balancing (SB)

- **Use the idea of self-play games to boost the performance [Huang et al'11].**
  - **Supervised plus reenforcement learning.**
  - **Feature set can be smaller.**
  - **Normally does not learn what moves are played in expert games, but how good or bad a position is.**
    - ▷ *Some forms of position evaluation.*
- **Results are extremely positive for 9 by 9 Go.**
  - **Against GNU Go 3.8 level 10.**
    - ▷ 59.3% *winning rate using MM against a good baseline of* 50%.
    - ▷ 62.6% *winning rate using SB against a good baseline program of* 50%.
- **Results are not as good on 19 by 19 Go against one using MM along.**
- **Erica, a computer Go program, later improved the SB ideas in [Huang et al'11] won 2010 Computer Olympiad 19x19 Go Gold medal.**

How they were used then

- **Assume using the BT model.**
- **Generation of the pattern database:**
  - **Manually construct.**
  - **Exhaustive enumeration: small patterns such as 3 by 3.**
  - **Find patterns happened more than a certain number of times in the training set.**
    - ▷ *Patterns, for example diamond-shapes, are too large to enumerate.*
- **Training.**
- **Setting of the parameters:**
  - **Assume after training, feature or pattern i has a strength θ_i.**
  - **Let the current position be P with b possible child positions $P_1, \ldots, P_b$.**
  - **Let F_i be the features or patterns occurred in P_i.**
  - **Let the score of P_i be $S_i = \Pi_{j \in F_i} \theta_j$.**
- **Child P_j is chosen with the probability $\frac{S_j}{\sum_{i=1}^{b} S_i}$.**
  - ▷ *The best child is one with the largest score.*

Comments

- **Implementation:**
  - Incrementally update the features and patterns found.
  - Use some variations of the Zobrist hash function to efficiently find the strength of a feature or pattern.
- **We only show two possible avenues of using Bayesian network based learning via using the BT model, namely MM and SB.**
  - There are many other choices such Bayesian full ranking.
- **The training phase needs to be done once, but takes a huge amount of space and time.**
  - Usually use some forms of iterative updating algorithms to obtain the parameters, namely the strength vector, of the model.
  - For MM with k distinct features or patterns, n training positions and an average b legal moves for each position, it takes $O(kbn)$ space, and X iterations each of which takes $O(bnkh + k^2bn)$ time, where h is the size of the pattern or feature and X is the number of iterations needed for the approximation algorithm to converge [Coulum'07].
- **The prediction phase takes only $O(kh)$ space and time.**
- **Q: Can the part of feature extraction and weights of multiple features be done automatically?**

Artificial Neural Network

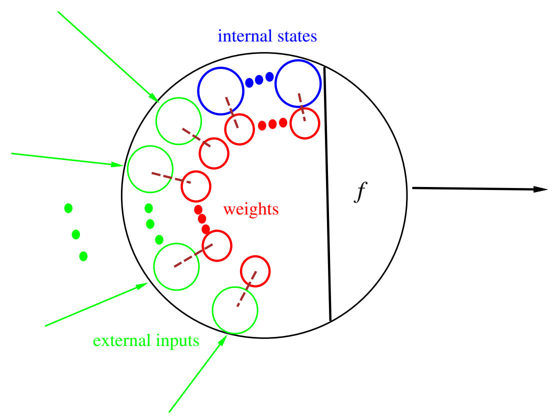
- **Using a complex network of neurons to better approximate non-linear optimizations.**
  - Usually called deep learning when the number of artificial neural network layers is more than 1.
  - Can have different architectures such as CNN or DNN.
- **A hot learning method inspired by the biological process of the animal visual cortex.**
  - Each neuron takes input from possibly overlaid neighboring sub-images of an image, and then assigns appropriate weights to each input plus some values within the cell to compute the output value.
  - This process can have multiple layers, namely a neuron's output can be other neurons' inputs, and forms a complex network.
  - Depending on the network structure, Bayesian network approaches tends to need less resources than the CNN or DNN approach.
  - There are also training phase and prediction phase.
- **Many different tools which can be parallelized using GPU.**
  - Need a great deal of resources to do training and some amount of time to do prediction.

Basics of ANN (1/3)

- **Assume the ith neuron whose output is z_i takes m_i inputs $x_{i,1}, \ldots, x_{i,m_i}$, and has internal states $y_{i,1}, \ldots, y_{i,n_i}$.**
  - **We want to assign weights $w_{i,1}, \ldots, w_{i,m_i+n_i}$ so that**

$$z_i = f((w_{i,1} * x_{i,1}), ..., (w_{i,m_i} * x_{i,m_i}), (w_{i,m_i+1} * y_{i,1}), ..., (w_{i,m_i+n_i} * y_{i,n_i})),$$

    where f is a transformation/activation function that is not hard to compute.
- **Neurons are connected as a inter-connection network where outputs of neurons can be inputs of others.**



Basics of ANN (2/3)

- Sometime for simplicity

$$z_i = f(\sum_{j=1}^{m_i}(w_{i,j} * x_{i,j}) + \sum_{j=1}^{n_i}(w_{i,j+m_i} * y_{i,j})).$$

- f is often called activation function that normalize the value.
  - Examples:
    - ▷ ***Binary step:*** $f(x) = (x \leq 0)?0 : 1$
    - ▷ ***ReLU (Rectified Linear Unit):*** $f(x) = (x < 0)?0 : x$
    - ▷ ...
  - Desired properties in obtaining optimization and consistence:
    - ▷ ***Nonlinear***
    - ▷ ***Continuously differentiable***
    - ▷ ***Monotonic***
    - ▷ ...

Basics of ANN (3/3)

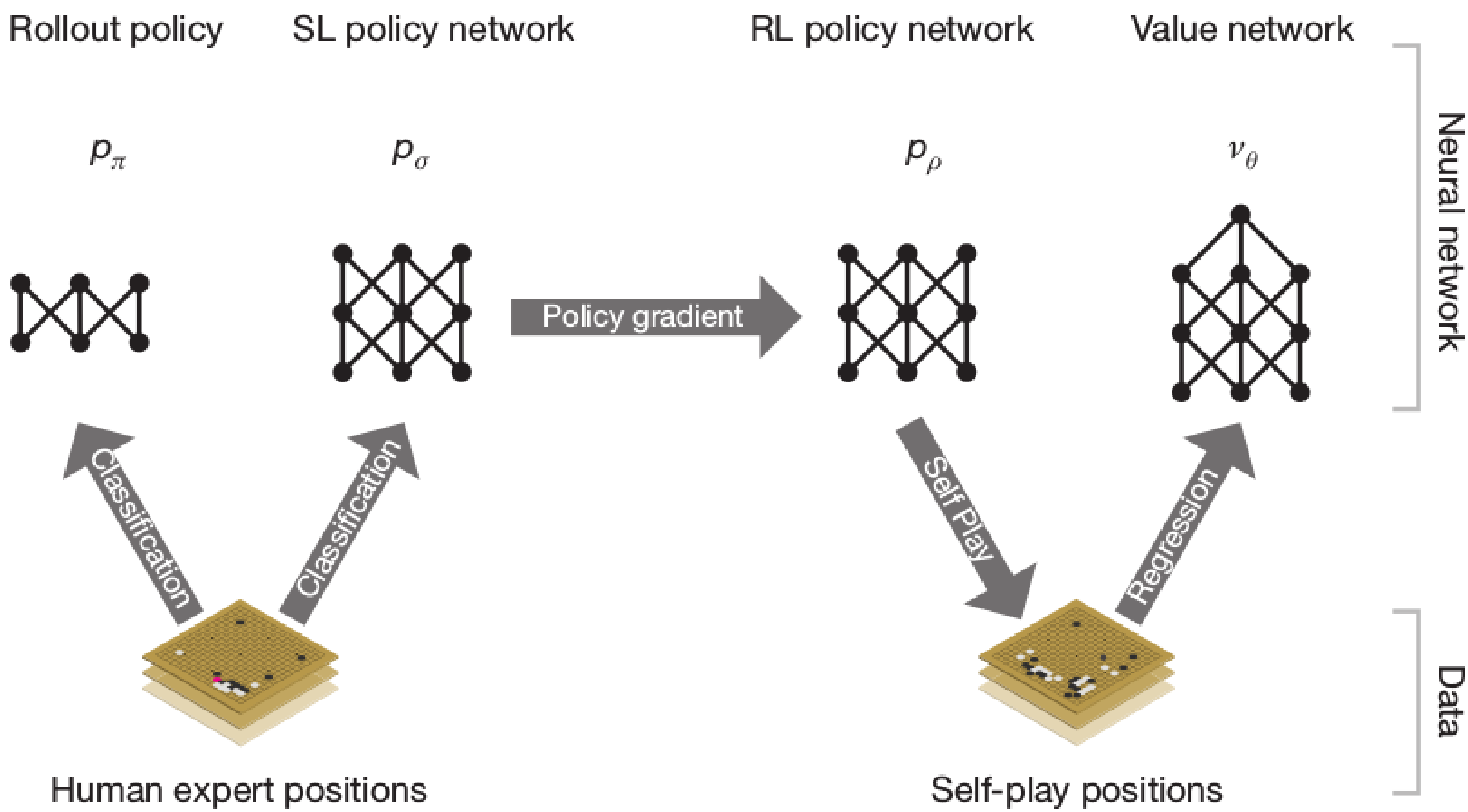
- Measurement of success
  - **Accuracy**: the percentage of your predicted values equal to their actual values.
    - *Accuracy may not be a good indicator of success since not all events, for example false positive and false negative, are equal.*
    - *Example: assume a rare event happened in a training set, then answering all negative's gives you a high accuracy, but useless prediction.*
- When there are multiple input data set, we want to find an assignment of the weights so that some **loss** or **error** function is minimized.
  - The loss or error function can be the average distance, in terms of L_1 or L_2 metric, among the training data set.
  - May want to use some log scale such as **cross entropy**.
- Many different algorithms exist to compute approximated values for the weights.
  - Computation time intensive.
  - Space usage intensive.

Deep learning

- Use artificial neural network of different sizes and structure to achieve different missions in playing 19 by 19 Go [Silver et al'16].
  - Supervised learning (SL) in building policy networks which spell out a probability distribution of possible next moves of a given position.
    - ▷ *A fast rollout policy: for the simulation phase of MCTS, prediction rate is 24.2% using only 2 μs.*
    - ▷ *A better SL rollout policy: 13-layer CNN with a prediction rate of 57.0% using 3 ms.*
  - Reinforcement learning (RL): obtain both a better, namely more accurate, policy network and at the same time a value network for position evaluation.
    - ▷ *RL policy: further training on the top of the previously obtained SL policy using more features and self-play games that achieves an 80% winning rate against the SL rollout policy.*
    - ▷ *Value network: using the RL policy to train for knowing how good or bad a position is.*

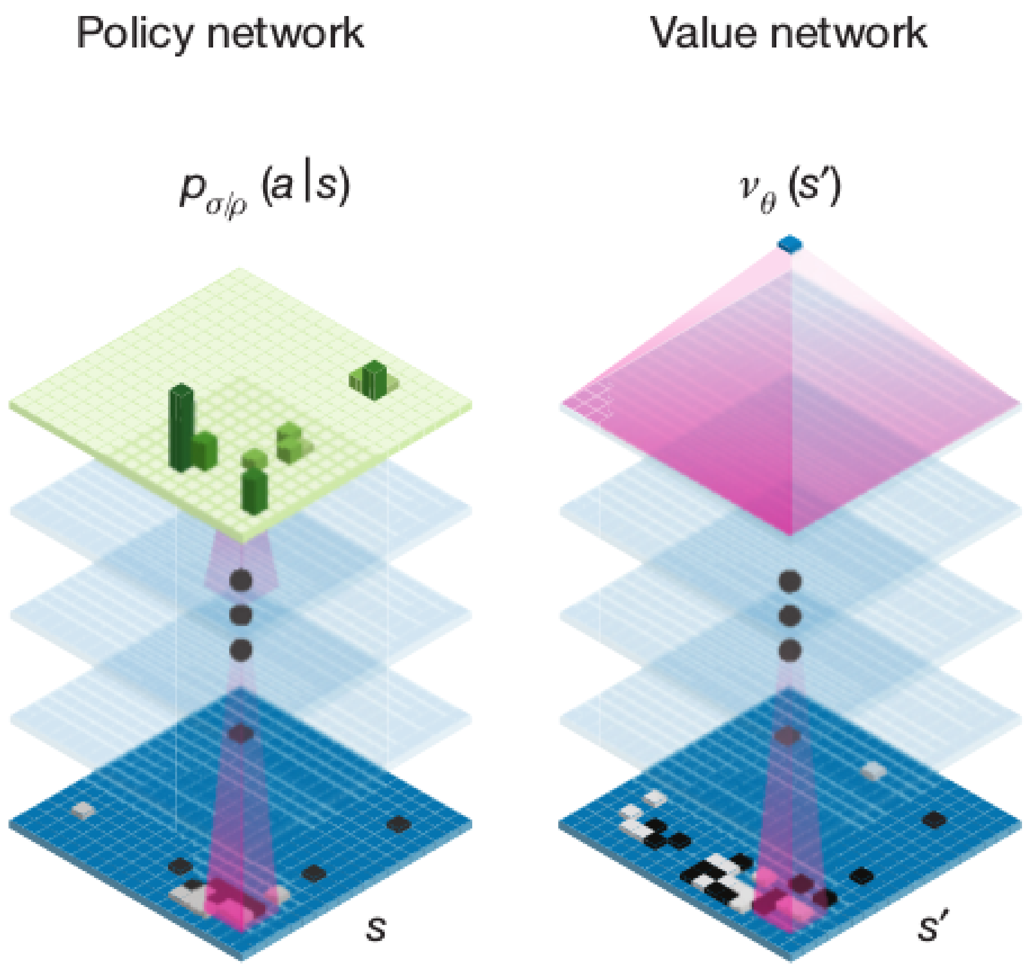
Various networks in AlphaGo

- **[Silver et al'16]**



How networks are obtained by AlphaGo

- **[Silver et al'16]**

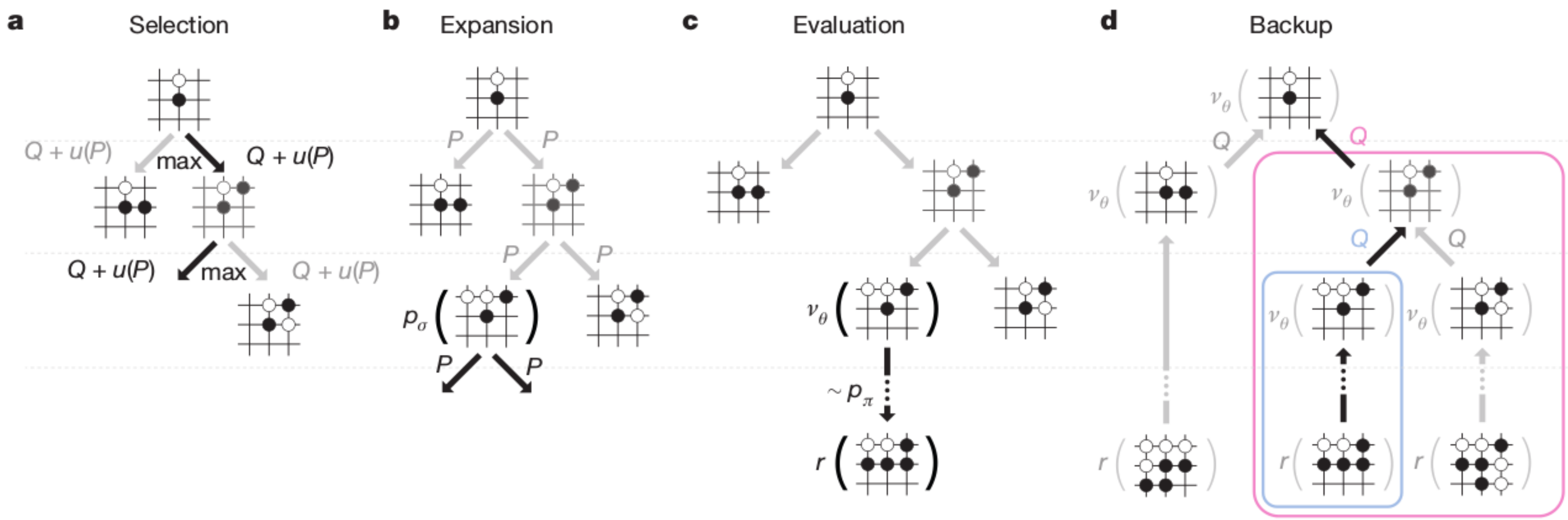


Combining networks

- Use a fast, but less accurate, SL Rollout policy to do the simulations.
  - Need to do lots of simulations.
- Use a slow, but more accurate, SL policy in the expansion phase.
  - Do not need to do node expansions too often.
- Use a slow, resource consuming and complex, but more informatic RL policy to construct the value network.
  - Do not need to do node evaluations too often.
- Using a combination of the output from the value network and the current score from the simulation phase, one can decide whether to end a simulation earlier or not.

How networks are used in AlphaGo

- **[Silver et al'16]**



Comments (1/3)

- **A very good tradeoff in performance and amount of resources used.**
  - **A less accurate but fast rollout policy is used with MCTS so that in the tree search part the correctness rate can be increased.**
    - ▷ *Need to do lots of simulations so each cannot take too much time.*
  - **Use a slow but more accurate policy for tasks such as expansion that do not need to carry out many times.**
  - **Use reinforcement learning in obtaining a value network to replace the role of designing complicated evaluation functions.**
- **Now is the way to go for computer Go!**
  - **Performance is extremely well and is generally considered to be over human champion.**
  - **Lots of legacy teams such as Zen and Crazystone are embracing ANN.**
  - **New teams such as Darkforest developed by Facebook, Fine Art developed by Tencent, and CGI developed by NCTU Taiwan, are catching up before 2016.**
- **Latest (after 2017)**
  - ▷ *Darkforest has turned open sourced in 2016.*
  - ▷ *After the introducing of AlphaGo Zero in 2017, it is difficult for others to catch up.*

Comments (2/3)

- **This approach can be used in many applications such as medical informatic which includes medical image and signal reading.**
  - **Anything that is pattern related and has lots of data collected with expert annotations.**
- **Take a lot of computing resources for computer Go.**
  - **More than 100,000 features and patterns.**
  - **More than 40 machines each with 32 cores and a total of more than 176 GPU cards whose power consumption is estimated to be in the order of 10^3 KW.**
  - **AlphaGo Zero claims to use much less resources.**
- **More studies are needed to lower the amount of resources used and to do transfer learning, namely duplicate the successful experience on one domain to another domain.**

Comments (3/3)

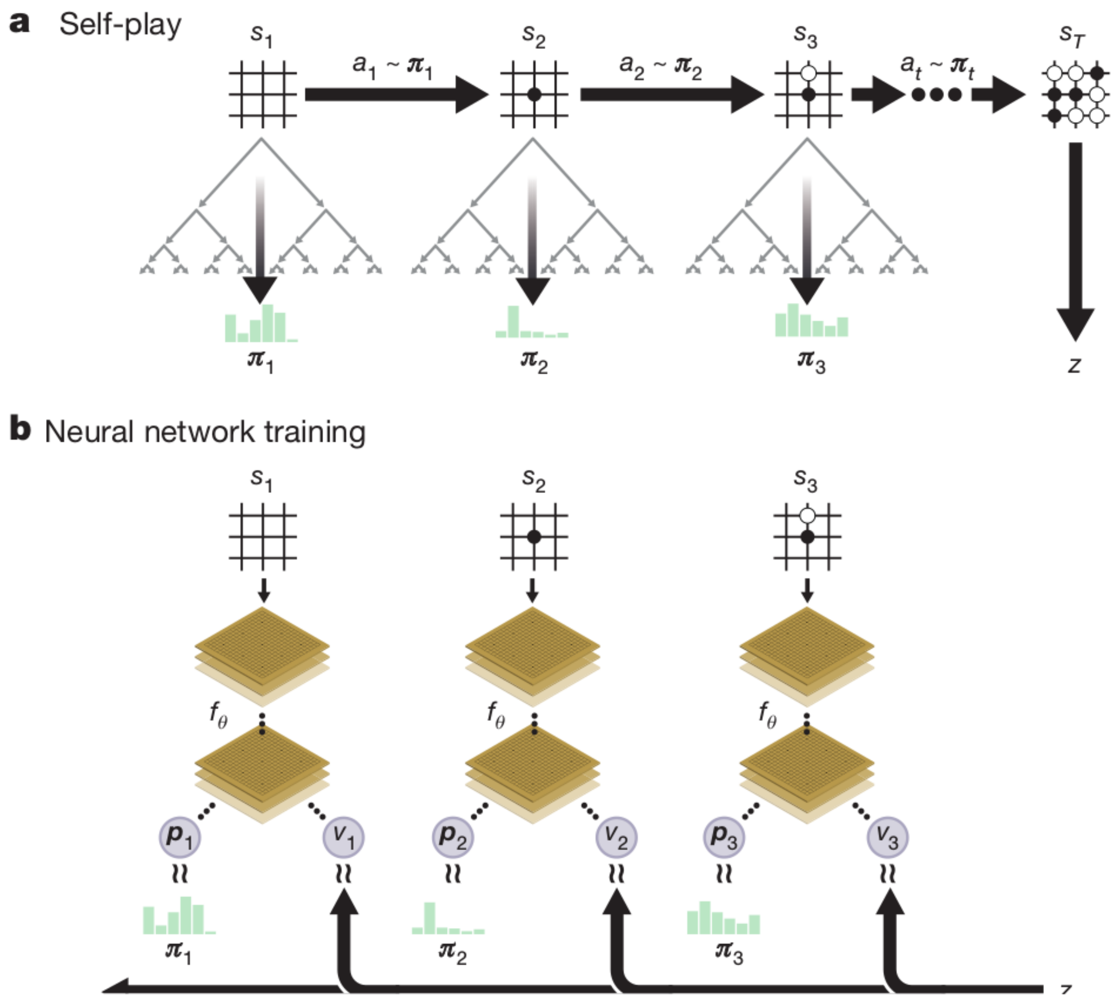
- **We only know it works by building the ANN, but it is almost impossible to explain how it works.**
  - **Very difficult to debug if a silly bug occurs.**
  - **Very difficult to "control" it to act the way you want/expect to.**
  - **It is an art to find the right coefficients and tradeoff.**
- **We also describe some fundamental techniques and ideas in the part of combining machine learning.**
  - **Other machine learning tools are also available and used.**
- **Using machine learning or MTCS along won't solve the performance problem in computer Go. However, the combination of both does the magic.**

AlphaGo Zero

- **Latest result: AlphaGo zero uses no supervised learning to achieves the top of computer Go at an Elo rating of 5185 [Silver et al. 2017].**
- **Main methods:**
  - **Trained solely by self-play reinforcement learning, starting from random play, without any supervision or use of human data.**
  - **Uses only the black and white stones from the board as input features.**
  - **Uses a single neural network, rather than separate policy and value networks.**
  - **Uses a simpler tree search that relies upon this single neural network to evaluate positions and sample moves, without performing any Monte Carlo rollouts.**
- **Contribution:**
  - **A new reinforcement learning algorithm that incorporates lookahead search inside the training loop, resulting in rapid improvement and precise and stable learning.**

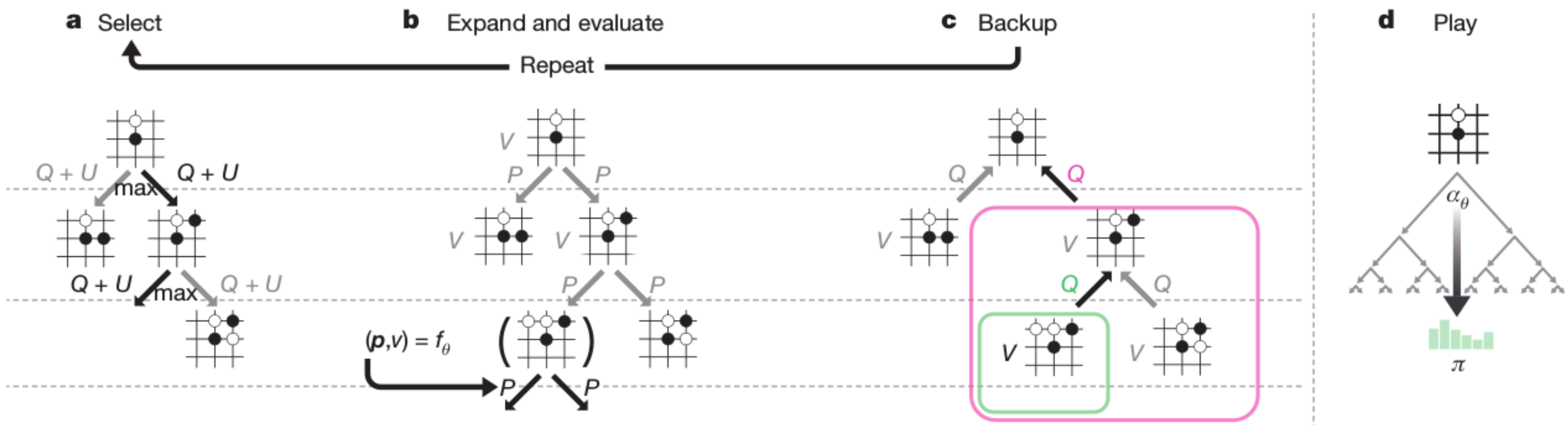
Training while self-playing

- **[Silver et al'17]**



MCTS and training together

- **[Silver et al'17]**



Comments

- Updating the network each ply you do in a self-play.
- Fast stabilizing in just 72 hours.
- Helped by special hardware and the total power consumption is greatly reduced.
  - A single machine with 4 TPU's.
- Is this a unique experience or something can be used in many other applications?

Alpha Zero (1/2)

- **A deep learning program to end all programs in game playing!**
  - **Starting from random play and given no domain knowledge except the game rules, Alpha Zero is a general algorithm that masters Chess, Go and Shogi.**
    - ▷ *No need to do supervised learning.*
    - ▷ *MCTS with deep learning beats alpha-beta with a human tuned evaluation function.*
  - **Claim to be as well for games with less-defined rules.**
    - ▷ *I tend to believe this is true!*
  - **"AlphaZero shows that it can learn that knowledge automatically – at least if you have Google's 5,000 TPUs, which is a lot of computing!" — Daylen Yang (a member of the Stockfish Chess program team) [Stetka'18].**
- **The Facebook PolyGames project tried to do a similar magic, but does not seem to be able to derive comparable performace.**

Alpha Zero (2/2)

- **Papers**
  - *Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm.*
    David Silver, Thomas Hubert, Julian Schrittwieser, Ioannis Antonoglou, Matthew Lai, Arthur Guez, Marc Lanctot, Laurent Sifre, Dharshan Kumaran, Thore Graepel, Timothy Lillicrap, Karen Simonyan, Demis Hassabis.
    arXiv:1712.01815, Dec. 5, 2017.
  - *A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play*
    David Silver, Thomas Hubert, Julian Schrittwieser, Ioannis Antonoglou, Matthew Lai, Arthur Guez, Marc Lanctot, Laurent Sifre, Dharshan Kumaran, Thore Graepel, Timothy Lillicrap, Karen Simonyan, Demis Hassabis.
    Science, 07 Dec 2018: 1140-1144.
  - *"Superhuman" AI Triumphs Playing the Toughest Board Games*
    Bret Stetka
    Scientific American, December 6, 2018.

MuZero

- **Be able to master sophicated games even without building the rules of the games into the learning network.**
  - **Be able to deduce the rule set by observing games palyed.**
  - **Be able to play master level Atari, Go, chess and shogi.**
- **Citation**
  - **Mastering Atari, Go, chess and shogi by planning with a learned model Julian Schrittwieser, Ioannis Antonoglou, Thomas Hubert, Karen Simonyan, Laurent Sifre, Simon Schmitt, Arthur Guez, Edward Lockhart, Demis Hassabis, Thore Graepel, Timothy Lillicrap & David Silver *Nature*, volume 588, pages 604–609 (2020)**

Comments (1/2)

- What can be done after MuZero?
  - It is better to know "what cannot be done using MuZero?"
- Beating the best human is only a very small, yet glorious, part of why we started doing Computer game playing researches.
  - A machine beats a human in a certain skill is predictable and inevitable for any skill that can be defined by a limited set of rules.
  - Machines, with a perfect duplicating capacity, are faster and more resourceful every day, but human only gets older and fade away.
- The real purpose of playing games using computers.
  - Enabling computers more useful to human.
    - ▷ *Programming and problem solving skills that can be used in other areas.*
    - ▷ *Helping human to have a better life.*
  - Understanding fundamental structures and properties of games.
    - ▷ *What properties do a game have?*
      Fairness Fun Educational Boundary effects
    - ▷ *What rules or designs to make a game having such properties?*
    - ▷ *Why this position is more difficult to human than others?*
    - ▷ *...*

Comments (2/2)

- **Skills with limited pre-defined rules, including low-level programming, are going to fade away.**
  - **Deep learning models are built for lots of complicated previously unsolvable exactly algorithms.**
  - **More examples:**
    - ▷ *What used to need coding in assembly/machine languages to achieve desirable performance 30 years ago are now replaced by high-level programming languages and maybe sometimes programming languages running in virtual machines or by interpreters.*
    - ▷ *What used to need coding for simple accounting functions 20 years ago are now replaced by simple spreadsheet softwares like EXCEL.*
    - ▷ *What are provided in the std:: library of C++17 are hard codings for most programmers before the year 2011.*
    - ▷ *Python, PHP, C# ...*
- **What is your role, as a human being, in the age of AI emerging or "disrupting"?**
  - **Are we at least part of the revolution or evolution?**

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