Zurich University
of Applied Sciences

AlphaZero: Learning Games from Selfplay

Datalab Seminar, ZHAW, November 14, 2018

Thilo Stadelmann

Outline

- Learning to act
- Example: DeepMind's Alpha Zero
- Training the policy/value network

Based on material by
- David Silver, DeepMind
- David Foster, Applied Data Science
- Surag Nair, Stanford University

Zurich University of Applied Sciences and Arts
InIT Institute of Applied Information Technology (stdm)

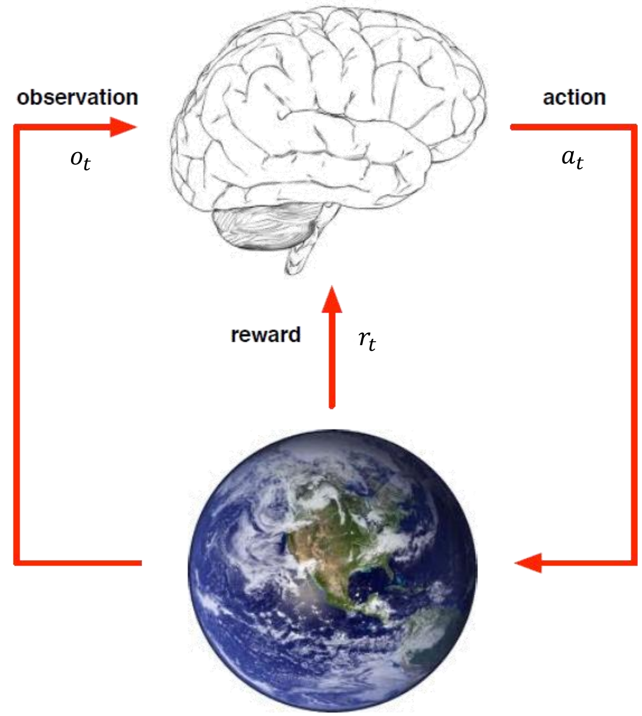
Teaser

See https://youtu.be/tXlM99xPQC8

1. LEARNING TO ACT

Reinforcement learning (RL)

Agent learns by interacting with a stochastic environment
➔ Science of sequential decision making

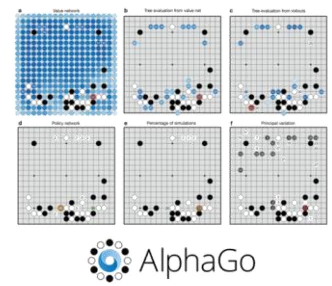


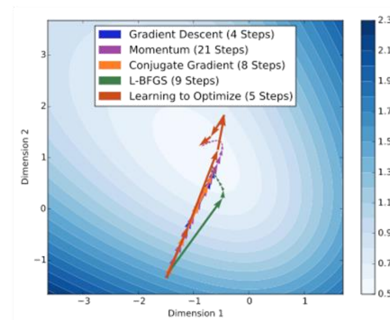
Many faces of reinforcement learning
- Optimal control (Engineering)
- Dynamic Programming (Operations Research)
- Reward systems (Neuro-science)
- Classical/Operant Conditioning (Psychology)

Characteristics
- No supervisor, only reward signals
- Feedback is delayed
- Trade-off between exploration & exploitation
- Sequential decisions: actions effect observations (non i.i.d.)

Application areas

- Automated vehicle control
  → An unmanned helicopter learning to fly and perform stunts
- Chat bots
  → Agent figuring out how to make a conversation
- Medical treatment planning
  → Planning a sequence of treatments based on the effect of past treatments
- **Game playing**
  → Playing backgammon, Atari Breakout, Tetris, Tic Tac Toe
- Data Center Cooling
  → https://deepmind.com/blog/deepmind-ai-reduces-google-data-centre-cooling-bill-40/
- Database query optimization
  → J. Ortiz et al., “Learning State Representations for Query Optimization with Deep Reinforcement Learning”, DEEM’2018
- Learning new machine learning algorithms
  → https://bair.berkeley.edu/blog/2017/09/12/learning-to-optimize-with-rl/





…and more
→ see https://www.oreilly.com/ideas/practical-applications-of-reinforcement-learning-in-industry,
https://www.meetup.com/de-DE/Reinforcement-Learning-Zurich/

2. EXAMPLE: DEEPMIND’S ALPHA ZERO

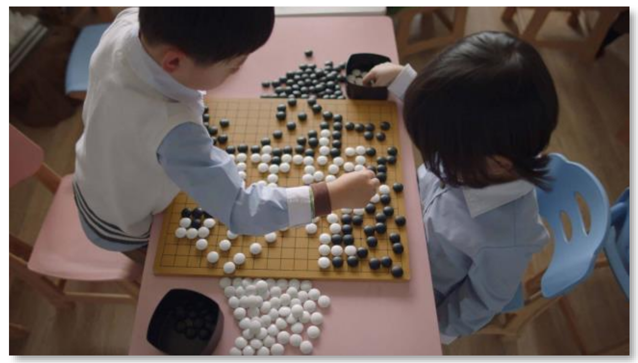
The game of Go

Properties

- **Perfect-information**, **deterministic**, two-player, turn-based, zero-sum game
- Played on a 19x19 board, alternate moves between black and white
- Two possible results: win or loss
- Considered a grand challenge for AI due to **vast search space** ($\sim 10^{170}$ states; chess: 10^{50})

Rules

- Each turn, a **stone** of the player's color is **put on** an **intersection** of the board (**or "pass"**)
- A stone (or **connected group** of stones) fully and **directly surrounded** by stones of the other color **is removed** from the board ("captured")
- It is not allowed to recreate a former board position
- **Two** consecutive **passes end the game**
- The player having **more "area" wins**



AlphaGo, AlphaGo Zero & Alpha Zero

ARTICLE

doi:10.1038/nature24270

Mastering the game of Go without human knowledge

David Silver[1]*, Julian Schrittwieser[1]*, Karen Simonyan[1]*, Ioannis Antonoglou[1], Aja Huang[1], Arthur Guez[1], Thomas Hubert[1], Lucas Baker[1], Matthew Lai[1], Adrian Bolton[1], Yutian Chen[1], Timothy Lillicrap[1], Fan Hui[1], Laurent Sifre[1], George van den Driessche[1], Thore Graepel[1] & Demis Hassabis[1]

A long-standing goal of artificial intelligence is an algorithm that learns, *tabula rasa*, superhuman proficiency in challenging domains. Recently, AlphaGo became the first program to defeat a world champion in the game of Go. The tree search in AlphaGo evaluated positions and selected moves using deep neural networks. These neural networks were trained by supervised learning from human expert moves, and by reinforcement learning from self-play. Here we introduce an algorithm based solely on reinforcement learning, without human data, guidance or domain knowledge beyond game rules. AlphaGo becomes its own teacher: a neural network is trained to predict AlphaGo's own move selections and also the winner of AlphaGo's games. This neural network improves the strength of the tree search, resulting in higher quality move selection and stronger self-play in the next iteration. Starting *tabula rasa*, our new program AlphaGo Zero achieved superhuman performance, winning 100–0 against the previously published, champion-defeating AlphaGo.

arXiv:1712.01815v1 [cs.AI] 5 Dec 2017

Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm

David Silver,[1*] Thomas Hubert,[1*] Julian Schrittwieser,[1*] Ioannis Antonoglou,[1] Matthew Lai,[1] Arthur Guez,[1] Marc Lanctot,[1] Laurent Sifre,[1] Dharshan Kumaran,[1] Thore Graepel,[1] Timothy Lillicrap,[1] Karen Simonyan,[1] Demis Hassabis[1]

[1]DeepMind, 6 Pancras Square, London N1C 4AG.

*These authors contributed equally to this work.

Abstract

The game of chess is the most widely-studied domain in the history of artificial intelligence. The strongest programs are based on a combination of sophisticated search techniques, domain-specific adaptations, and handcrafted evaluation functions that have been refined by human experts over several decades. In contrast, the *AlphaGo Zero* program recently achieved superhuman performance in the game of Go, by *tabula rasa* reinforcement learning from games of self-play. In this paper, we generalise this approach into a single *AlphaZero* algorithm that can achieve, *tabula rasa*, superhuman performance in many challenging domains. Starting from random play, and given no domain knowledge except the game rules, *AlphaZero* achieved within 24 hours a superhuman level of play in the games of chess and shogi (Japanese chess) as well as Go, and convincingly defeated a world-champion program in each case.

The study of computer chess is as old as computer science itself. Babbage, Turing, Shannon, and von Neumann devised hardware, algorithms and theory to analyse and play the game of chess. Chess subsequently became the grand challenge task for a generation of artificial intelligence researchers, culminating in high-performance computer chess programs that perform at superhuman level (*9, 13*). However, these systems are highly tuned to their domain, and cannot be generalised to other problems without significant human effort.

A long-standing ambition of artificial intelligence has been to create programs that can instead learn for themselves from first principles (*26*). Recently, the *AlphaGo Zero* algorithm achieved superhuman performance in the game of Go, by representing Go knowledge using deep convolutional neural networks (*22, 28*), trained solely by reinforcement learning from games of self-play (*29*). In this paper, we apply a similar but fully generic algorithm, which we

1

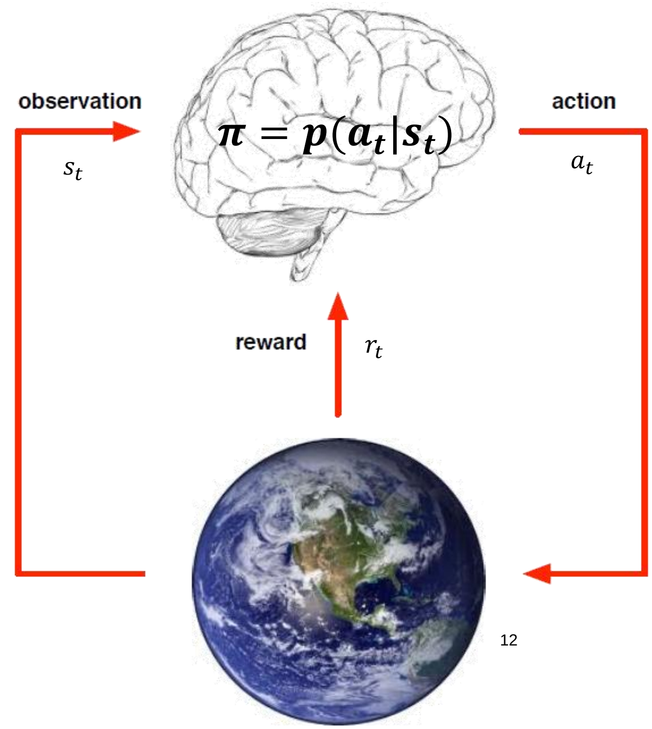
Interesting: playing strength ⇧, generality ⇧, complexity ⇩ (over time)

Goal: a policy

Policy

- Policy $\pi = p\ (a_t|s_t)$ maps (probabilistically) from the current state s_t to action a_t
  ➔ can be represented by a **function approximator** (e.g., a neural network)

- Given the optimal policy π^*, one can behave optimally in the environment
  ➔ but optimality in complex strategic situations is difficult to achieve
  ➔ **lookahead search** makes **tactic**al behavior easier

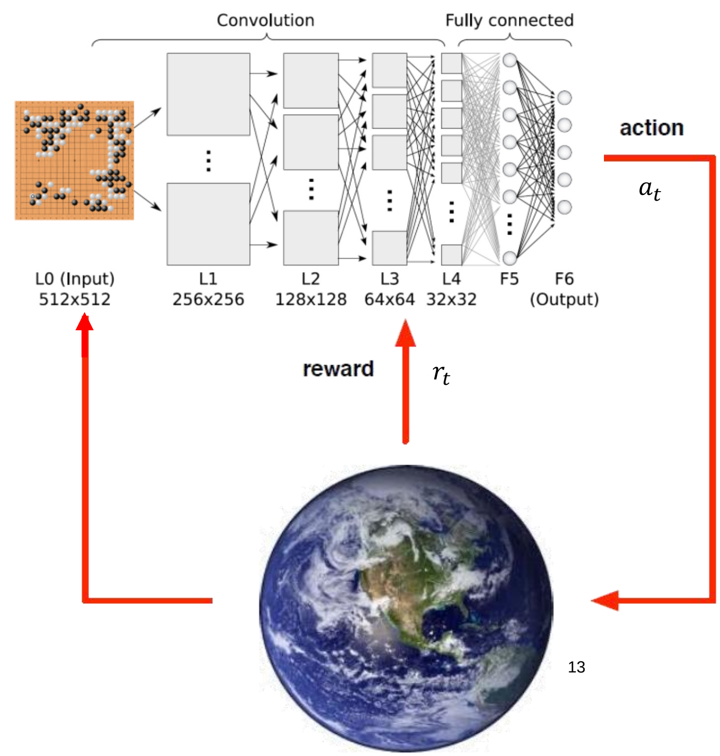


Goal: a policy

Policy

- Policy $\pi = p\ (a_t|s_t)$ maps (probabilistically) from the current state s_t to action a_t
  ➔ can be represented by a **function approximator** (e.g., a neural network)

- Given the optimal policy π^*, one can behave optimally in the environment
  ➔ but optimality in complex strategic situations is difficult to achieve
  ➔ **lookahead search** makes **tactic**al behavior easier

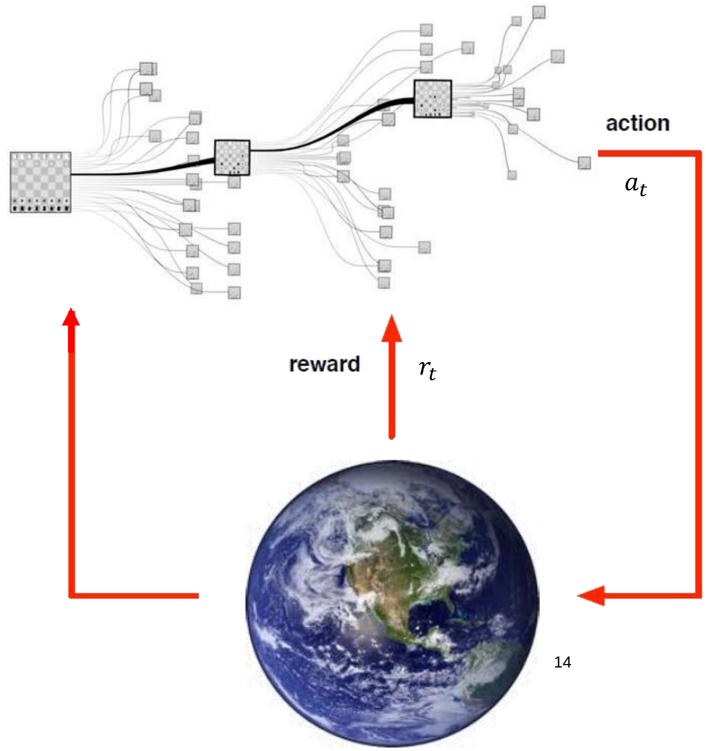


Goal: a policy

Policy

- Policy $\pi = p\,(a_t|s_t)$ maps (probabilistically) from the current state s_t to action a_t
  ➔ can be represented by a **function approximator** (e.g., a neural network)

- Given the optimal policy π^*, one can behave optimally in the environment
  ➔ but optimality in complex strategic situations is difficult to achieve
  ➔ **lookahead search** makes **tactic**al behavior easier



Using a learned policy in Alpha Zero

I.e., play a move given a policy

Goal

- In state s_t, chose next move a_t

Ingredients

- **Neural network** $\vec{p}, \mathrm{v} = f_\theta(s_t)$ that outputs two quantities
  - Policy vector $\vec{p}$ (a distribution over all possible actions)
  - Value v (an estimate of the probability of winning from this state)

  ➔ **intuition**
- **Monte Carlo Tree Search** (MCTS) to build ad hoc search tree
  - MC: tree not fully grown → only **likely branches** get explored
  - (Chosen branch can be reused for next move for computational savings)

  ➔ **tactics**

How to chose each move

- Perform MCTS search on ad-hoc built tree
  (using neural network for initial intuition if a move is good → see next slide)
- Play move most often taken by search ($\max(N)$)

Perform a MCTS search
I.e., provide the basis for a move

- Create (empty or partly re-used) tree with root s_t

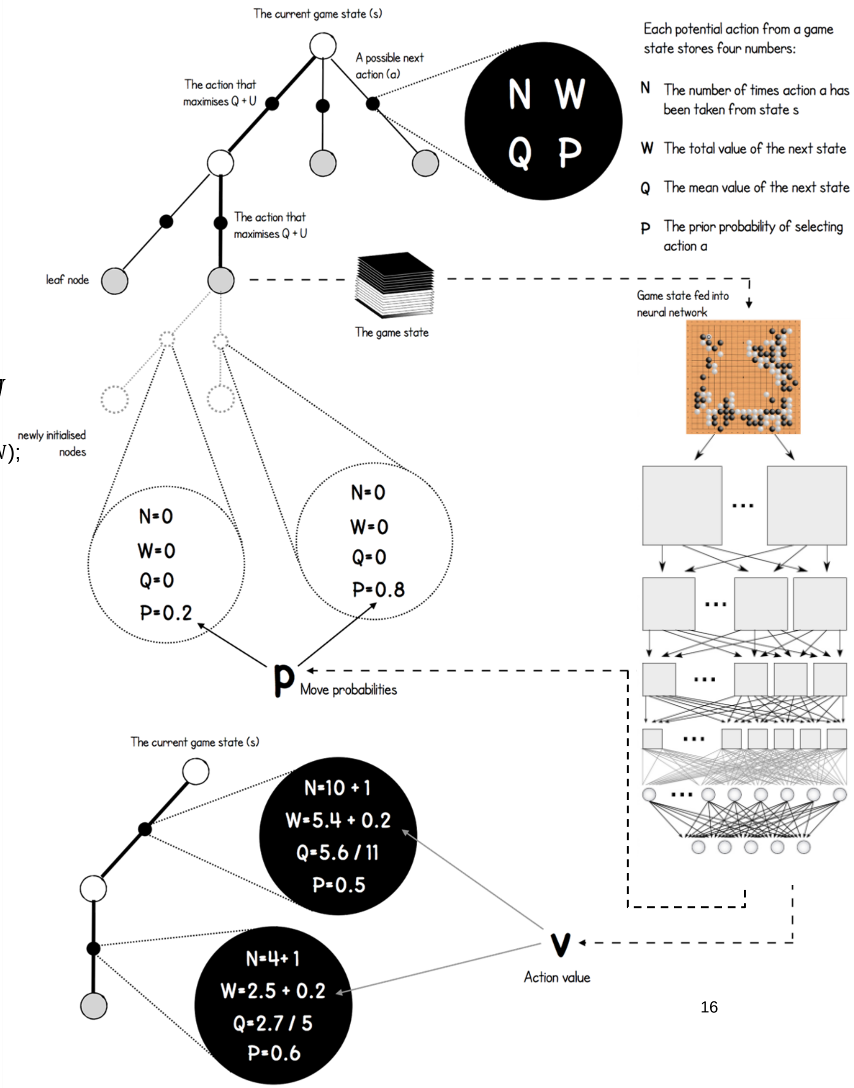
- Perform 1,600 simulations:
  (one simulation = one traversal of current tree until yet unexpanded leaf node or terminal node is hit)

  1. Start at $s = s_t$

  2. Traverse tree:
     while s is not a leaf node: choose a that maximizes $Q + U$
     (Q is the current mean value of s over all simulations in this search;
     U is high if s has high prior probability p from the neural net, or hasn't been explored much (small N);
     ➔ U dominates at the beginning of a search; as the branch gets explored, Q becomes important)

  3. Expand tree: query neural net for $\vec{p}, \mathrm{v} = f_\theta(s)$
     $N = 0,\ W = 0,\ Q = 0,\ p = \vec{p}_a$

  4. Backup: update statistics of each visited node:
     $N = N + 1,\ W = W + \mathrm{v},\ Q = W/N$

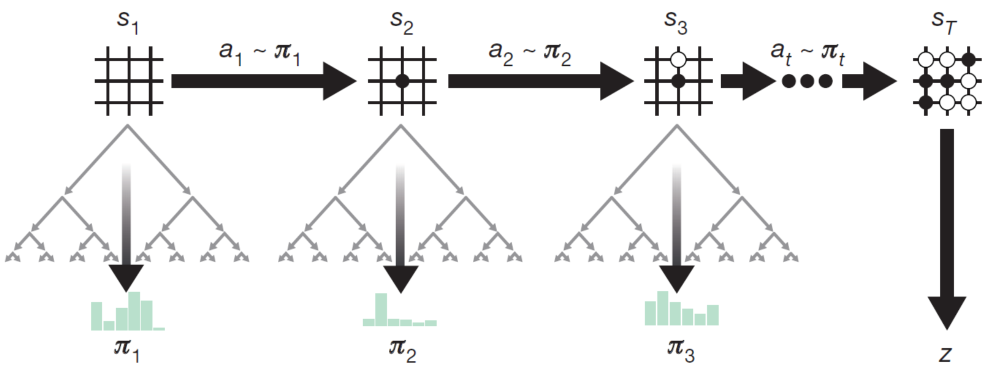


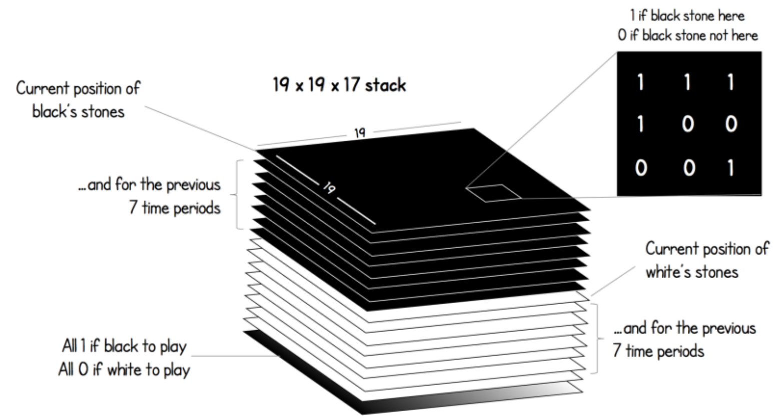
3. TRAINING THE POLICY/VALUE NETWORK

Create experience by selfplay
(=Evaluate the current policy)

1. Initialize f_θ randomly

2. Play 25,000 games against yourself
   - Use MCTS and current best f_θ for both player's moves
   - **For each move**, **store**
     - **game state** (see figure →),
     - **search probabilities** from MCTS ($\pi_t \sim N$ for all actions of s_t),
     - **winner** ($z = \pm 1$ from perspective of current player)



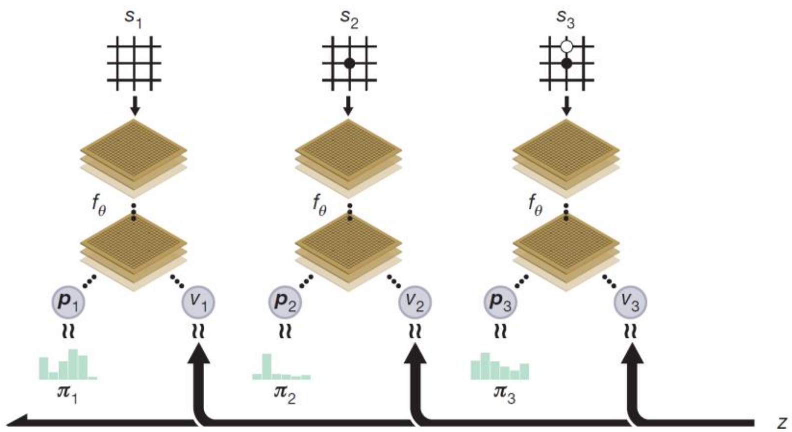


3. Trigger retraining (→ see next slide), goto 2

Retrain neural network
(=Improve the current policy)

1. Experience replay: sample mini-batch of 2,048 positions from last 500,000 self-play games

2. Retrain f_θ on this batch using **supervised learning**:
   - **Input:** game states
   - **Output:** move-probabilities p (dropping vector notation for simplicity), value v
   - **Labels:** search-probabilities π, actual winner z
   - **Loss:** cross-entropy between p, π $+$ MSE between v, z $+$ L_2-regularization of θ



3. Trigger evaluation (→ see next slide) after 1,000 training loops, goto 2

Evaluate current network

1. Play 400 games between current best vs. latest f_θ
   - **Choose each move by MCTS** and respective network
   - **Play deterministically** (no additional exploration → see below)

After 1,600 simulations, the move can either be chosen:

Deterministically (for competitive play)
Choose the action from the current state with greatest **N**

Stochastically (for exploratory play)
Choose the action from the current state from the distribution

$$\pi \sim N^{1/\tau}$$

where τ is a temperature parameter, controlling exploration

2. Replace best network with latest f_θ if the latest wins $\geq 55\%$ of matches

Important RL concepts showcased here
To be detailed elsewhere

- Formal framework: **Markov decision processes** (MPDs)
- The RL problem: observations vs. **states**, learning vs. **planning**, **prediction & control**
- Ingredients to a solution: **model**, **value function** (v: state-value / q: action-value), **policy**
- Methods: **dynamic programming** (**policy iteration**), **Monte Carlo**, temporal difference learning

- RL & function approximation: general instability, **experience replay**, **target networks**
- Exploration vs. exploitation: **optimistic initialization** (**upper confidence bounds**), noise on priors

Where's the intelligence?
Man vs. machine

- Alpha(Go) Zero **learns** without human intervention **from scratch** (pure selfplay & the rules)
  → strong point for capabilities of RL
- Alpha(Go) Zero is considerably more **simple/principled** than previous approaches
  → good ideas are usually simple and intuitively right (the reverse is not necessarily true!)
- Recently*, OpenAI showed similar **fascinating performance** on Dota2, and DeepMind on Quake III Arena**
  → RL has made big progress and seems fit for real applications beyond simulations

- Yet***, solutions are still hand-crafted per use case and suffer from extreme **sample inefficiency** and **training instabilities**
  → Training takes very long even on server hardware, debugging is frustrating, success is fragile

*) See https://blog.openai.com/openai-five/ and https://blog.openai.com/learning-dexterity/
**) See https://deepmind.com/blog/capture-the-flag/
***) See https://www.alexirpan.com/2018/02/14/rl-hard.html and http://amid.fish/reproducing-deep-rl

Review

- **Reinforcement learning** (RL) is “**learning to act**” – a general method for “**sequential decision making**”
- Most notable **differences** from unsupervised & supervised **ML**:
  - **no “data set”**
  - agent learns from interaction with environment and sparse rewards
    → less learning signal
    → **experience** is highly correlated and **not i.i.d.**!
    → yet:

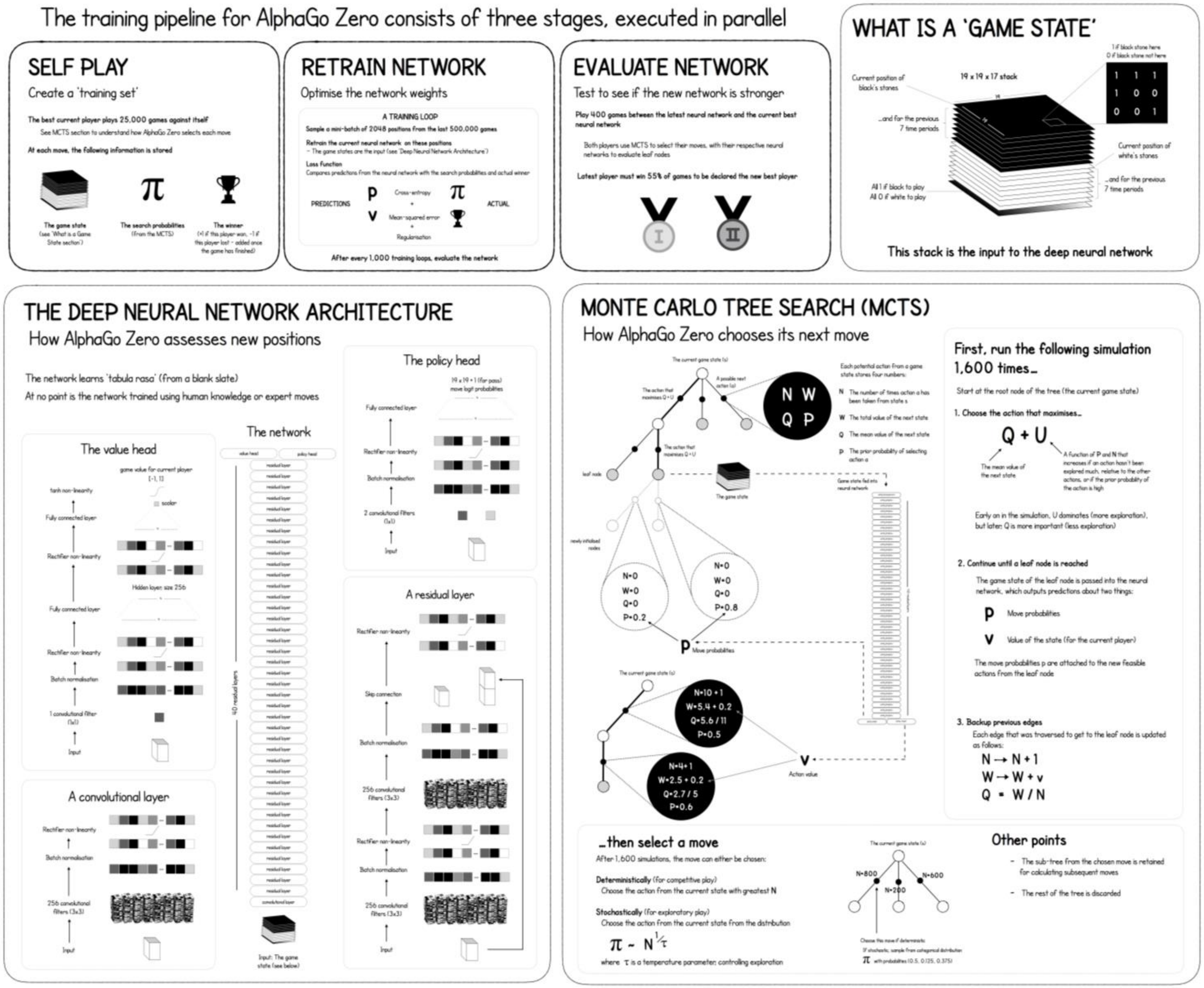
- **Alpha Zero** uses an elegant RL algorithm based on
  - **selfplay** (for experience generation)
  - **MCTS** tree search (to plan ahead in a principled way)
  - function approximation using **deep learning** (to use intuition about board states to guide/focus the tree search)
- Read the original publication, it is worth it (clear, concise, precise, complete): https://www.nature.com/articles/nature24270

Zurich University
of Applied Sciences

APPENDIX

Alpha Zero overview

Source: https://medium.com/applied-data-science/alphago-zero-explained-in-one-diagram-365f5abf67e0



Pseudo code – training π

Source: https://web.stanford.edu/~surag/posts/alphazero.html

```
def policyIterSP(game):
    nnet = initNNet() #initialise random neural network
    examples = []
    for i in range(numIters):
        for e in range(numEps):
            #collect examples from this game
            examples += executeEpisode(game, nnet)
        new_nnet = trainNNet(examples)
        #compare new net with previous net
        frac_win = pit(new_nnet, nnet)
        if frac_win > threshold:
            nnet = new_nnet #replace with new net
    return nnet
```

```
def executeEpisode(game, nnet):
    examples = []
    s = game.startState()
    mcts = MCTS() #initialise search tree

    while True:
        for _ in range(numMCTSSims):
            mcts.search(s, game, nnet)
        #rewards can not be determined yet
        examples.append([s, mcts.pi(s), None])
        #sample action from improved policy
        a = random.choice(len(mcts.pi(s)), p=mcts.pi(s))
        s = game.nextState(s,a)
        if game.gameEnded(s):
            examples = assignRewards(examples, game.gameReward(s))
            return examples
```

```
def search(s, game, nnet):
    if game.gameEnded(s): return -game.gameReward(s)

    if s not in visited:
        visited.add(s)
        P[s], v = nnet.predict(s)
        return -v

    max_u, best_a = -float("inf"), -1
    for a in range(game.getValidActions(s)):
        u = Q[s][a] + c_puct*P[s][a]*sqrt(sum(N[s]))/(1+N[s][a])
        if u>max_u:
            max_u = u
            best_a = a
    a = best_a

    sp = game.nextState(s, a)
    v = search(sp, game, nnet)

    Q[s][a] = (N[s][a]*Q[s][a] + v)/(N[s][a]+1)
    N[s][a] += 1
    return -v
```