Artificial Intelligence

12. General Game Playing

One AI to Play All Games and Win Them All

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Summer Term 2019

Thanks to Dr. Peter Kissmann for slide sources

Agenda

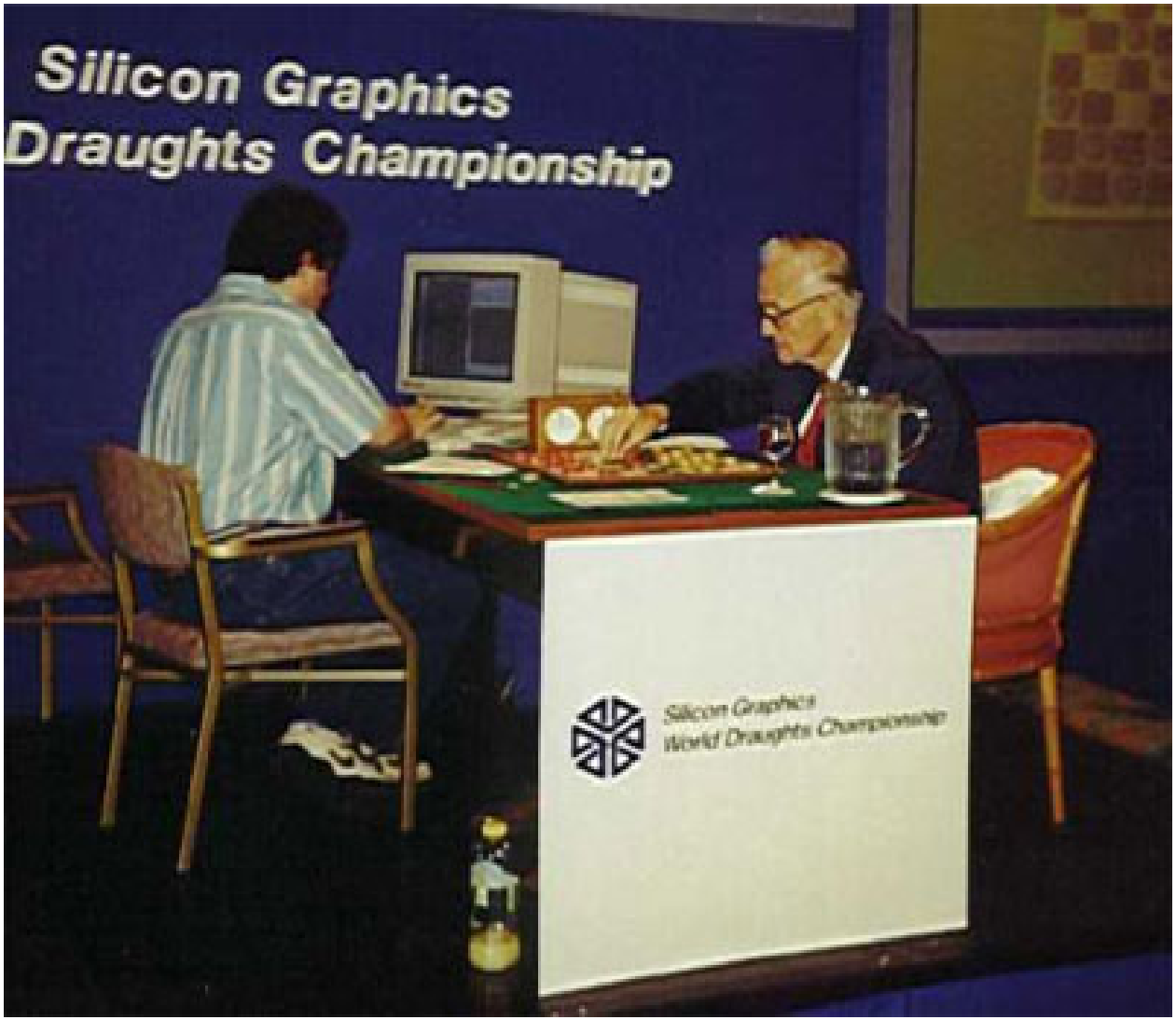
1. Introduction
2. The Game Description Language (GDL)
3. Playing General Games
4. Learning Evaluation Functions: Alpha Zero
5. Conclusion

Deep Blue Versus Garry Kasparov (1997)

Games That *Deep Blue* Can Play

1. Chess

Chinook Versus Marion Tinsley (1992)

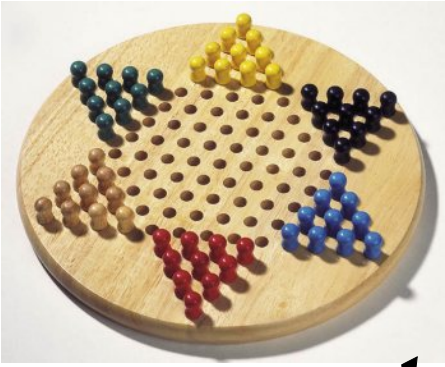


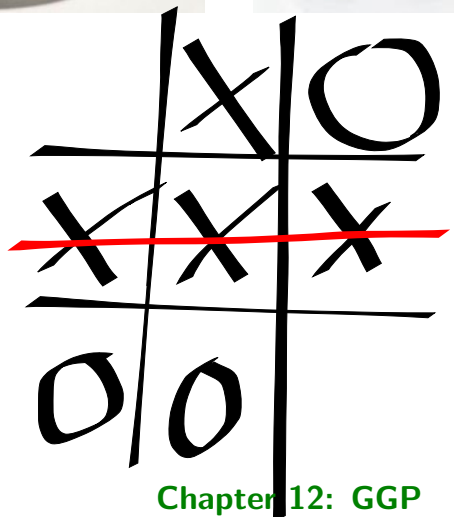
Games That *Chinook* Can Play

1. Checkers

Games That a General Game Player Can Play

1. Chess
2. Checkers
3. Chinese Checkers
4. Connect Four
5. Tic-Tac-Toe
6. ...





Games That a General Game Player Can Play (Ctd.)

5. ...
6. Othello
7. Nine Men's Morris
8. 15-Puzzle
9. Nim
10. Sudoku
11. Pentago
12. Blocker
13. Breakthrough
14. Lights Out
15. Amazons
16. Knightazons
17. Blocksworld
18. Zhadu
19. Pancakes
20. Quarto
21. Knight's Tour
22. n-Queens
23. Blob Wars
24. Bomberman (simplified)
25. Catch a Mouse
26. Chomp
27. Gomoku
28. Hex
29. Cubicup
30. ...

Games That a General Game Player Can Play (Ctd.)

94. ...
95. Bidding Tic-Tac-Toe
96. 9-Board Tic-Tac-Toe
97. Finding the way out of a labyrinth
98. Rock-Paper-Scissors
99. Iterated Prisoner's Dilemma

And many, many more...

General Game Playing

General game players can

- read and process arbitrary game descriptions
- play efficiently based on the game descriptions

Difference to specialized players (such as *Deep Blue*, *Chinook*, etc.):

General game players

- have no special knowledge about game at hand
- must establish any knowledge on their own

How *General* are General Games?

Nowadays: Game Description Language (GDL) [Love *et al.* (2008)]

Difference to Adversarial Search

- Any number of players (≥ 1)
- Simultaneous move games only (turn-taking games modeled by use of *noops*, i.e., moves that do not change the current state)
- Rewards integers in [0,100] for all players; not necessarily zero-sum

Some Limitations Remain

- finite
- discrete
- deterministic (i.e., no games of chance such as dice games)
- full information for all players (i.e., prohibits most card games)

Last two points covered by GDL-II (GDL for Incomplete Information) [Thielscher (2010)], though rarely used.

How to Describe a General Game?

Adversarial Search Game State Space

Recall: $\Theta = (S, A, T, I, S^T, u)$ (S: states/positions, A: actions/moves, T: transition relation, I: initial state, S^T: terminal states, u: utility function).

Minimal Requirements in GGP

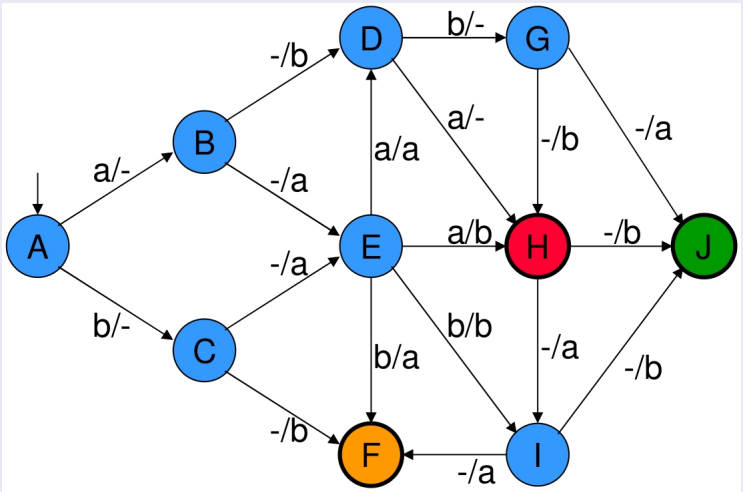
- State description
- Number of players
- Initial state
- Legal moves (for all players given current state) – the actions/moves
- Successor generation (given current state and all players' moves) – the transition relation
- Termination (given current state)
- Rewards (for all players given current state) – the utility

How to Describe a General Game? (Ctd.)

Full State Space

Problems:

- State-space explosion problem
  - *Tic-Tac-Toe*: $5{,}478$
  - *Connect Four*: $4{,}531{,}985{,}219{,}092 \approx 4.5 \times 10^{12}$
  - *15-Puzzle*: $10{,}461{,}394{,}944{,}000 \approx 10^{13}$
- Thus, immense memory requirement $\rightarrow$ not practical



Alternative: Logical Input (Declarative Description)

Much more compact; easier to use for analysis.
Here, *Game Description Language* (GDL) used [Love *et al.* (2008)]

The Game Description Language (GDL) – States

Representation of States

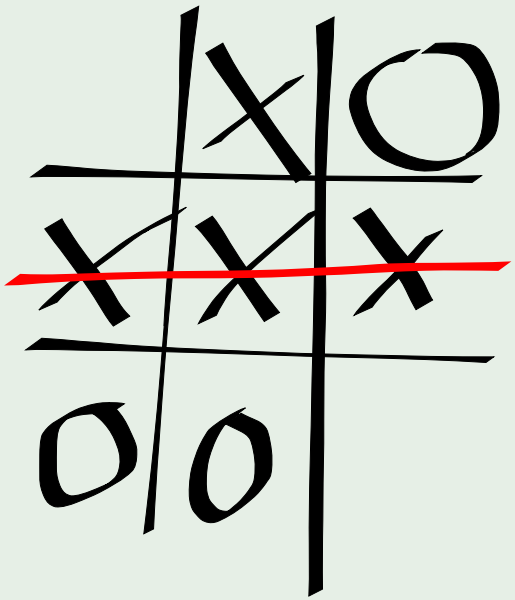
States represented by set of predicates of the form

```
(true <fact>)
```

meaning that `<fact>` is true in the current state.

Example (Tic-Tac-Toe)

```
{(true (cell 1 1 o)),
(true (cell 2 1 o)),
(true (cell 3 1 b)),
(true (cell 1 2 x)),
(true (cell 2 2 x)),
(true (cell 3 2 x)),
(true (cell 1 3 b)),
(true (cell 2 3 x)),
(true (cell 3 3 o))}
```



GDL – Rules

Rules in GDL

GDL based on *Datalog*. It uses (logical) *rules*. A rule is a kind of implication consisting of a head predicate and a body, which in turn consists of a number of predicates `<body_1>`, ..., `<body_n>`:

```
(<head> ⇐
    <body_1>
    ...
    <body_n>
)
```

- head is true if every part of body is true or body is empty.
- predicates can have arguments; may be constants or variables, latter denoted by prefix '?'
- in evaluation, a variable can be replaced by any constant, but all appearances of a variable in one rule must be replaced by the same constant.

GDL – Rules (Ctd.)

Example (Tic-Tac-Toe)

```
((row ?r ?p) ⇐                    Row ?r completely marked with ?p
    (true (cell 1 ?r ?p))
    (true (cell 2 ?r ?p))         if every cell in that row
    (true (cell 3 ?r ?p))         marked with ?p
)
```

Evaluation with our state for ?r = 1 and ?p = o:

Example (Tic-Tac-Toe)

```
((row 1 o) ⇐
    (true (cell 1 1 o))
    (true (cell 2 1 o))
    (true (cell 3 1 o))
)
```

```
{(true (cell 1 1 o)),
(true (cell 2 1 o)),
(true (cell 3 1 b)),
(true (cell 1 2 x)),
(true (cell 2 2 x)),
(true (cell 3 2 x)),
(true (cell 1 3 b)),
(true (cell 2 3 x)),
(true (cell 3 3 o))}
```

GDL – Rules (Ctd.)

Example (Tic-Tac-Toe)

```
((row ?r ?p) ⇐                    Row ?r completely marked with ?p
    (true (cell 1 ?r ?p))
    (true (cell 2 ?r ?p))         if every cell in that row
    (true (cell 3 ?r ?p))         marked with ?p
)
```

Evaluation with our state for ?r = 2 and ?p = x:

Example (Tic-Tac-Toe)

```
((row 2 x) ⇐
    (true (cell 1 2 x))
    (true (cell 2 2 x))
    (true (cell 3 2 x))
)
```

```
{(true (cell 1 1 o)),
(true (cell 2 1 o)),
(true (cell 3 1 b)),
(true (cell 1 2 x)),
(true (cell 2 2 x)),
(true (cell 3 2 x)),
(true (cell 1 3 b)),
(true (cell 2 3 x)),
(true (cell 3 3 o))}
```

GDL – Rules (Ctd.)

We can also iterate such rules.

Example (Tic-Tac-Toe)

`((line ?p) ⇐ (row ?r ?p))`	Line of three equal symbols `?p`, if some row `?r` has 3 `?p`, or
`((line ?p) ⇐ (column ?c ?p))`	some column `?c` has 3 `?p`, or
`((line ?p) ⇐ (diagonal ?p))`	some diagonal has 3 `?p`.

To evaluate `line`, we first must evaluate `row`. We already know that `(row 2 x)` holds, so `(line x)` holds as well.

GDL – Players

Players

For each player, a rule of the form

```
(role <player>)
```

must be specified.

Example (Tic-Tac-Toe)

```
(role xplayer)
(role oplayer)
```

Thus, we have two players, `xplayer` and `oplayer`

GDL – Initial State

Initial State

Set of all rules of the form

```
(init <fact>)
```

build the initial state (each such `<fact>` holds).

Example (Tic-Tac-Toe)

`(init (cell 1 1 b))`	Board
`...`	initially
`(init (cell 3 3 b))`	empty (`b`)
`(init (control xplayer))`	`xplayer` is starting player

Note: `control` is no GDL keyword; the player has to derive the connection between this fact and the player to move automatically.

GDL – Initial State (Ctd.)

In evaluation of rules we need `true` predicates:
To set the current state to the initial one, we must transform all `(init <fact>)` to `(true <fact>)` in our internal representation

Example (Tic-Tac-Toe)

```
(init (cell 1 1 b))                 {(true (cell 1 1 b)),
(init (cell 2 1 b))                 (true (cell 2 1 b)),
(init (cell 3 1 b))                 (true (cell 3 1 b)),
(init (cell 1 2 b))                 (true (cell 1 2 b)),
(init (cell 2 2 b))                 (true (cell 2 2 b)),
(init (cell 3 2 b))        ⇒        (true (cell 3 2 b)),
(init (cell 1 3 b))                 (true (cell 1 3 b)),
(init (cell 2 3 b))                 (true (cell 2 3 b)),
(init (cell 3 3 b))                 (true (cell 3 3 b)),
(init (control xplayer))            (true (control xplayer))}
```

GDL – Legal Moves

Legal Moves

A <player> can perform a certain <move> if the body of a rule

```
((legal <player> <move>) ⇐ <body>)
```

is evaluated to true.

Example (Tic-Tac-Toe)

```
((legal xplayer (mark ?x ?y)) ⇐
    (true (control xplayer))
    (true (cell ?x ?y b))
)
```

xplayer may mark cell (x, y), if it is xplayer's turn to move and cell (x, y) is currently empty (b).

Example (Tic-Tac-Toe)

```
((legal oplayer noop) ⇐
    (true (control xplayer))
)
```

oplayer may do nothing (noop), if it is xplayer's turn to move. Note: noop is no GDL keyword.

GDL – Chosen Moves

Representation of Chosen Moves

When we know that a <player> chose to perform some <move> we add a predicate of the form

```
(does <player> <move>)
```

to our internal representation of the current state.

Example (Tic-Tac-Toe)

```
{(true (cell 1 1 b)),
(true (cell 2 1 b)),
(true (cell 3 1 b)),
(true (cell 1 2 b)),
(true (cell 2 2 b)),
(true (cell 3 2 b)),
(true (cell 1 3 b)),
(true (cell 2 3 b)),
(true (cell 3 3 b)),
(true (control xplayer))}
```

```
xplayer: (mark 1 1)
   oplayer: noop
```

$\Rightarrow$

```
{(true (cell 1 1 b)),
(true (cell 2 1 b)),
(true (cell 3 1 b)),
(true (cell 1 2 b)),
(true (cell 2 2 b)),
(true (cell 3 2 b)),
(true (cell 1 3 b)),
(true (cell 2 3 b)),
(true (cell 3 3 b)),
(true (control xplayer)),
(does xplayer (mark 1 1)),
(does oplayer noop)}
```

GDL – Successor Generation

Successor Generation

Each <fact> that will be true in the successor state must appear in the head of a next rule

((next <fact>) ⇐ <body>)

whose body is evaluated to true in the current state given the chosen moves.

Example (Tic-Tac-Toe)

```
((next (cell ?m ?n x)) ⇐
    (does xplayer (mark ?m ?n))
)
```

(m, n) will be marked with x, if xplayer chose to mark it now.

Example (Tic-Tac-Toe)

```
((next (control oplayer)) ⇐
    (true (control xplayer))
)
```

It will be oplayer's turn next, if it was xplayer's turn now.

GDL – Successor Generation (Ctd.)

Important

Everything that can be derived from the `next` rules is true in the successor state.
Nothing else is true in the successor state.

Example (Tic-Tac-Toe)

If we have only one `next` rule:

```
((next (cell ?m ?n x)) ⇐
    (does xplayer (mark ?m ?n)))
```

If the `xplayer` chose to `(mark 1 1)`, we know that in the successor state `(true (cell 1 1 x))` holds.
However, nothing else holds – there is no memory involved. The old state is completely discarded and the successor state created based only on the outcome of the `next` rules.

GDL – Successor Generation (Ctd.)

Important

Thus, it is necessary that all things that do not change are explicitly modeled as well.

Example (Tic-Tac-Toe)

```
((next (cell ?m ?n x)) ⇐
    (true (cell ?m ?n x))
)
((next (cell ?m ?n o)) ⇐
    (true (cell ?m ?n o))
)
```

In the next state a cell will remain marked with x, if it is marked so in the current state. Same for o.

GDL – Successor Generation (Ctd.)

Generating Successor State

Having evaluated the `next` rules, we must store the successor state as the new current state.

Example (Tic-Tac-Toe)

```
{(true (cell 1 1 b)),
(true (cell 2 1 b)),
(true (cell 3 1 b)),
(true (cell 1 2 b)),
(true (cell 2 2 b)),
(true (cell 3 2 b)),
(true (cell 1 3 b)),
(true (cell 2 3 b)),
(true (cell 3 3 b)),
(true (control xplayer)),
(does xplayer (mark 1 1)),
(does oplayer noop)}
```

evaluate next rules ⇒

```
{(next (cell 1 1 x)),
(next (cell 2 1 b)),
(next (cell 3 1 b)),
(next (cell 1 2 b)),
(next (cell 2 2 b)),
(next (cell 3 2 b)),
(next (cell 1 3 b)),
(next (cell 2 3 b)),
(next (cell 3 3 b)),
(next (control oplayer))}
```

set succ. state ⇒

```
{(true (cell 1 1 x)),
(true (cell 2 1 b)),
(true (cell 3 1 b)),
(true (cell 1 2 b)),
(true (cell 2 2 b)),
(true (cell 3 2 b)),
(true (cell 1 3 b)),
(true (cell 2 3 b)),
(true (cell 3 3 b)),
(true (control oplayer))}
```

GDL – Termination

Termination

The game ends when the body of any rule

(terminal ⇐ <body>)

is evaluated to true.

Example (Tic-Tac-Toe)

	The game ends, if
(terminal ⇐ (line x))	we have a line of 3 xs.
(terminal ⇐ (line o))	Or 3 os.
(terminal ⇐ (boardfilled))	Or no cell is empty anymore.

GDL – Rewards

Rewards

A <player> will get a specified <reward> if the body of a rule

((goal <player> <reward>) ⇐ <body>)

is evaluated to true.

In GDL, rewards are integers in the range [0,100], with 100 being best.

Example (Tic-Tac-Toe)

((goal xplayer 100) ⇐ (line x))

xplayer gets 100 points if we have a line of 3 xs on the board.

Example (Tic-Tac-Toe)

((goal oplayer 0) ⇐ (line x))

In the same situation, oplayer gets 0 points.

GDL – Rewards (Ctd.)

General games allow much more general outcomes than in our adversarial search setting:

- (partly) cooperative games (i.e., several players get same reward → should work together to achieve highest possible outcome)
- different rewards depending on actual outcome – not necessarily zero-sum
- classical zero-sum games – here in the form of constant-sum games (the sums of the players' rewards always sum up to 100).

To transform zero-sum game from GGP setting to our adversarial search setting: Set utility to reward(first player) – reward(second player)

Example – Chomp

Reminder: Minimal Requirements

- State description
- Number of players
- Initial state
- Legal moves
- Successor generation
- Termination
- Rewards

```
(role eater)
(role muncher)

(init (chocolate 1 1)) [...]  (init (chocolate 8 7))
(init (control eater))

((legal ?player (bite ?x ?y)) ⇐
    (true (control ?player))
    (true (chocolate ?x ?y)))

((legal eater noop) ⇐ (true (control muncher)))
((legal muncher noop) ⇐ (true (control eater)))

((next (chocolate ?x ?y)) ⇐
    (true (chocolate ?x ?y))
    (does ?player (bite ?i ?j))
    (less_than ?x ?i))

((next (chocolate ?x ?y)) ⇐
    (true (chocolate ?x ?y))
    (does ?player (bite ?i ?j))
    (less_than ?y ?j))

((next (control eater)) ⇐ (true (control muncher)))
((next (control muncher)) ⇐ (true (control eater)))

((next (poisoned ?p)) ⇐ (does ?p (bite 1 1)))

(terminal ⇐ (true (poisoned ?p)))

((goal eater 100) ⇐ (true (poisoned muncher)))
((goal muncher 100) ⇐ (true (poisoned eater)))

((goal ?player 0) ⇐ (true (poisoned ?player)))

((less_than ?n ?m) ⇐ (succ ?n ?m))
((less_than ?n ?m) ⇐
    (succ ?k ?m)
    (less_than ?n ?k))

(succ 1 2) [...]  (succ 7 8)
```

Example – Chomp (Ctd.)

Side-Remark

Chomp is won by the starting player – no matter the size of the rectangular board.
Proof by strategy-stealing argument:

- Assume, the second player had a winning strategy
- Then that one must be able to find a winning move for every possible first move
- Assume that the first player bites only one piece (i.e., the top-right position)
- With this we know that the second player must have a winning move
- However, any move that the second player can play here could have been played by the first player in the initial state
- Thus, it must be the first player who has such a winning strategy

How Does GGP Work?

1. GGP server sends game description + `starttime` + `movetime` to players
2. players have `starttime` seconds for initial evaluation
3. players have `movetime` seconds for evaluation, then send `move` to server
4. server updates state
5. if `terminal`, goto step 9
6. server informs all players about all performed moves
7. players update their current state
8. continue with step 3
9. server sends `STOP` along with the chosen moves to all players; game ends

Let's Play a Game

http://ggpserver.general-game-playing.de

- Current form of GGP introduced around 2005 by Games-group of Stanford University
- Since 2005 annual GGP competitions at top-level AI conferences

Question!

What algorithm would you use for GGP:

1. Minimax
2. AlphaBeta
3. MCTS

Playing General Games

In earliest competitions (2005 and 2006) most successful players performed Alpha-Beta search. Alpha-Beta quite general but:...

- only defined for two-player turn-taking zero-sum games
- difficult to find reasonable automatically generated evaluation function (cannot use expert knowledge)

Rules of Chess $\rightarrow$ Pawn (Bauer) 1, Knight (Springer) 3, Bishop (Läufer) 3, Rook (Turm) 5, Queen (Dame) 9.

Since 2007 all winners of competition used UCT: though there is still a lot of margin of improvement ...

Lack of Evaluation Functions: Learning to the Rescue

(description of a game in modeling language)

training phase

(current position)

(knowledge about the game) $\Rightarrow$ general game player

(play)

Alpha Zero

Chess	Go	Shogi
1997	2016	2017
DeepBlue vs. Kasparov	AlphaGo vs. Lee Sedol	Bonanza vs. 9-dan

2017: AlphaZero trains itself in a few hours to play chess, go, and shogi.

Then, it defeats current best programs:

- Chess: Stockfish[1] (+28, =72, -0)
- Go: AlphaGoZero (+60, -40)
- Shogi: Elmo (+90, =2, -8)

[1] Not 100% clear if the setting was fair for Stockfish.

From Alpha Go to Leela Zero

Common aspects: combine MCTS and Neural Networks

- AlphaGo: specialized program to play Go
  - Used games from Go profesionals as training data
  - Several neural networks with a complicated architecture
- AlphaZero: common architecture for Chess, Go, and Shogi
  - Simpler than AlphaGo: a single neural network per game
  - Reinforcement learning from scratch without additional training data
  - But: not open source and only published partial data, used TPU's
- Leela Zero: open-source version of AlphaZero
  - Standard hardware (CPU and GPU)
  - LeelaChessZero won the TCEC Season 15 in May'19 (after training for more than a year, more than 200 million games.)

AlphaGo: Overview

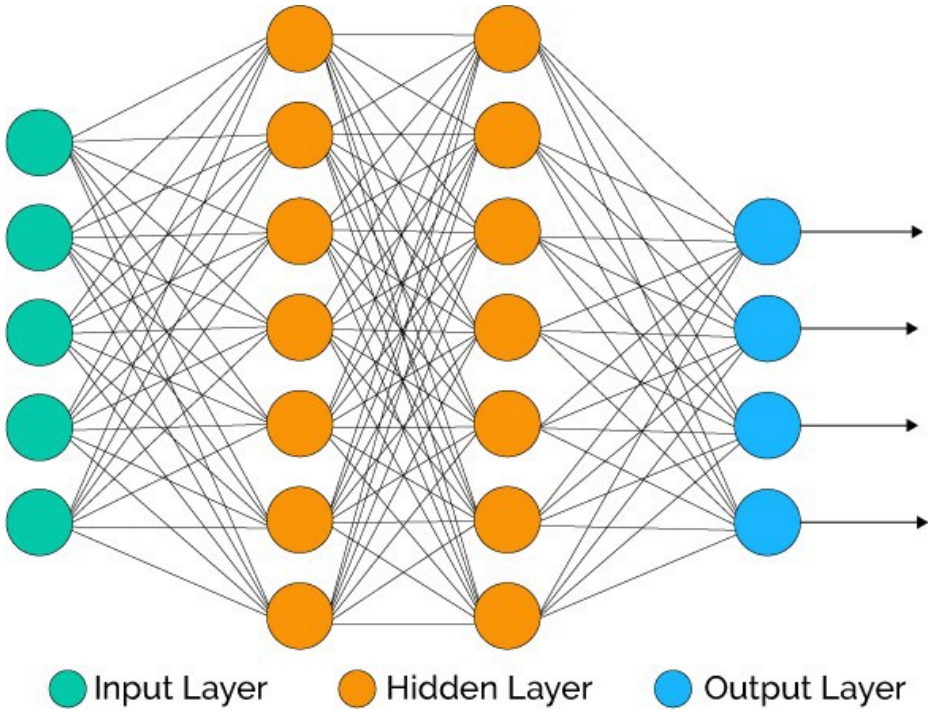
Neural Networks:

- Policy networks: Given a state s, output a probability distibution over the actions applicable in s.
- Value networks: Given a state s, outpout a number estimating the game value of s.

Combination with MCTS:

- Policy networks bias the action choices within the MCTS tree (and hence the leaf-state selection), and bias the random samples.
- Value networks are an additional source of state values in the MCTS tree, along with the random samples.

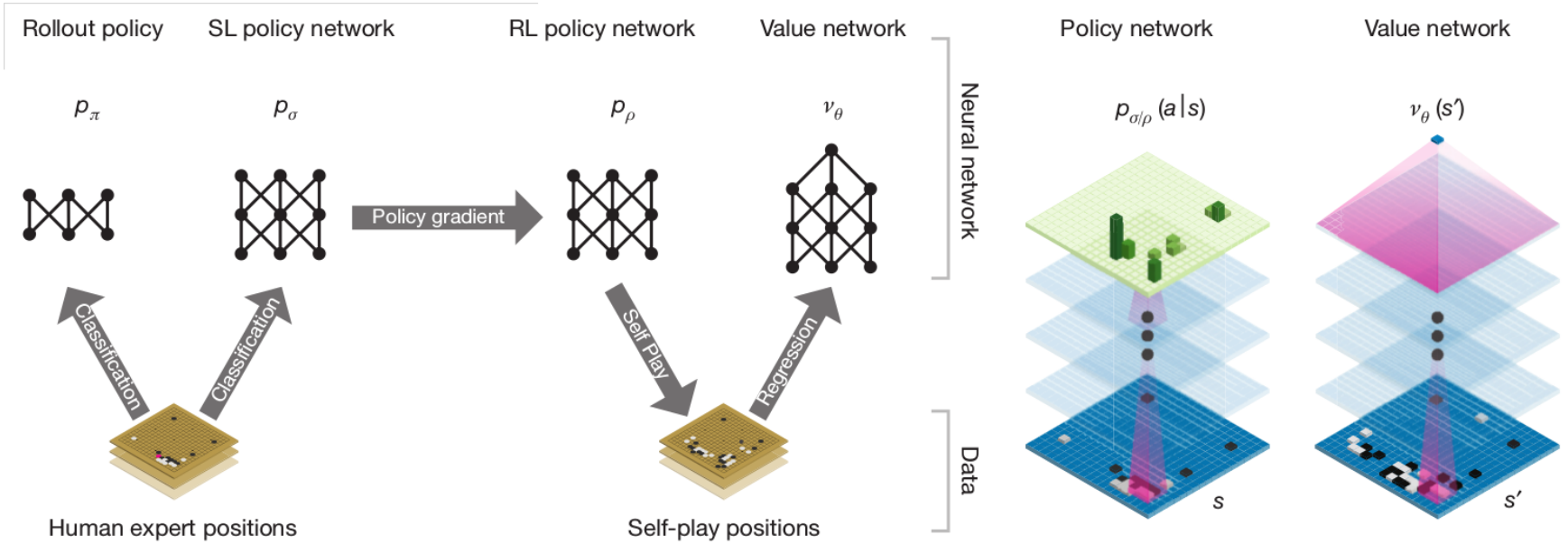
Neural Networks



- Input layer: Description of the game state
- Output layer: What we want to predict (e.g. utility of the state in value networks, probability of a in policy networks)
- Supervised Learning: Given a set of training data (positions for which we know their utility), configure the net so that the error is minimized for those positions.

Neural Networks in AlphaGo

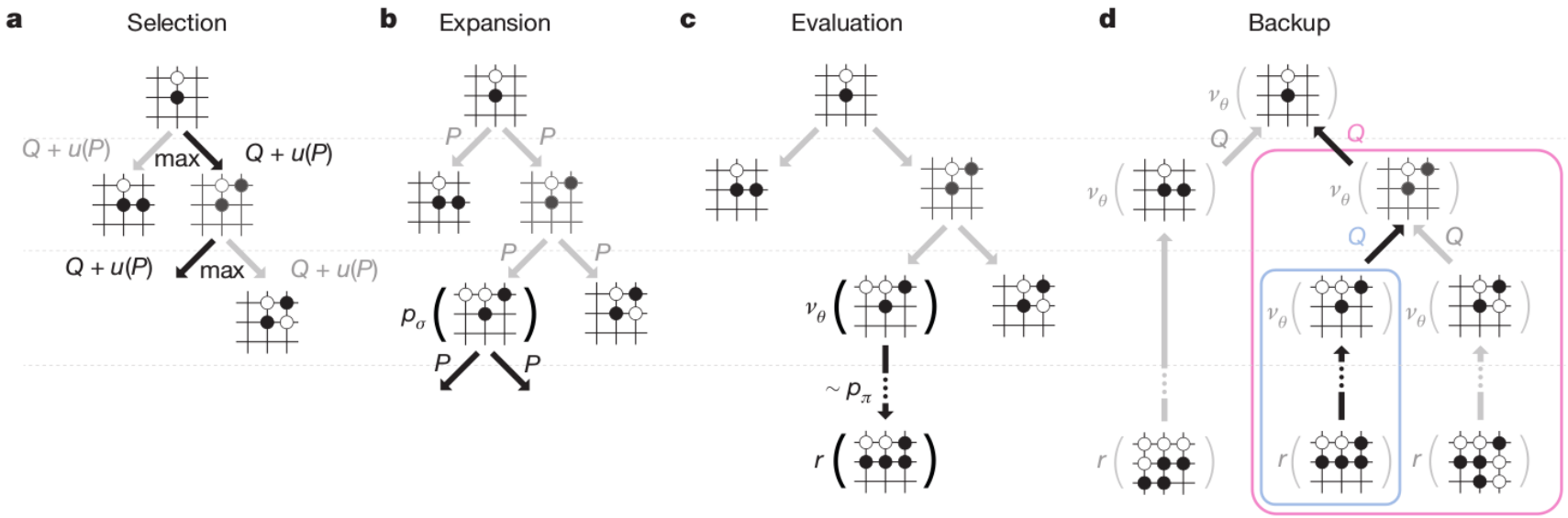
Illustration: (taken from [Silver *et al.* (2016)])



- *Rollout policy* p_π*:* Simple but fast, $\approx$ prior work on Go.
- *SL policy network* p_σ*:* Supervised learning, human-expert data ("learn to choose an expert action").
- *RL policy network* p_ρ*:* Reinforcement learning, self-play ("learn to win").
- *Value network* v_θ*:* Use self-play games with p_ρ as training data for game-position evaluation v_θ ("predict which player will win in this state").

Neural Networks + MCTS in AlphaGo

Illustration: (taken from [Silver *et al.* (2016)])



- *Rollout policy* p_π*:* Action choice in random samples.
- *SL policy network* p_σ*:* Action choice bias within the UCTS tree (stored as "P", gets smaller to "$u(P)$" with number of visits); along with quality Q.
- *RL policy network* p_ρ*:* Not used here (used only to learn v_θ).
- *Value network* v_θ*:* Used to evaluate leaf states s, in linear sum with the value returned by a random sample on s.

Alpha Zero: MCTS

- Neural Network: function $f(s)$ that returns $p_a = P(a|s)$ for all $a \in A$, plus expected utility from position s.
- Run Monte-Carlo Tree Search with the following modifications:
  - In leaf nodes, the neural network is evaluated (no random play until end of the game).
  - When traversing the tree, the probability of choosing a depends on p_a, apart from the number of times that a was previously selected and the estimated utility of its outcome.
- Why not use Alpha Beta with such an evaluation function?

  $\rightarrow$Taking average of evaluation function reduces the impact of the "noise" in the learnt evaluation function

Alpha Zero: Training Phase

- Goal: Learn function $f(s)$ that returns $p_a = P(a|s)$ for all $a \in A$, plus expected utility from position s.
- f is learnt by playing games against itself. After each game, f is updated to:
  1. Minimize the error between expected and real outcome.
  2. Minimize the difference between p_a and probability of a to be selected by MCTS in s.
- Requires very little domain knowledge:
  - Rules of the game (BlackBox formulation)
  - The neural network architecture is matched to the grid-structure of the board (in a non trivial way)
  - The typical number of legal moves is used to scale exploration noise
  - Long games are considered draws

AlphaZero, Conclusion?

Opinions?

- **My 5 cents:** Definitely a great achievement.
- Lots of questions to explore. OpenSource project for Go (https://github.com/leela-zero/leela-zero) and chess(`http://lczero.org/`)
- "Search + neural networks" looks like a great formula for general problem solving.

  → I expect lots of research on this in the coming decade(s). (In FAI, amongst others.)
- AlphaZero for GGP?
  AlphaZero is simpler than AlphaGo but its design is still quite intricate (architecture, neural network architectures, ...).

  → Still some human expertise in here.

  → How much of this is reusable in/generalizes to other problems?

Summary

- GGP is an extension of classical search problems and adversarial search problems: Support for any number of players, simultaneous moves and non-zero-sum utilities.
- Programmer does not know which game will be played, thus domain-independent algorithms must be used (no expert knowledge).
- Game Description Language GDL used for concise description of general games.

Discussion

- Alpha-Beta used early on. Later, change of paradigm to simulation-based search (UCT) – very fast and no expert knowledge needed.
- However, UCT bad if many *traps* in search space
- Research in general evaluation functions not far enough to beat UCT based players consistently
- Several ways overcoming this in current research:
  - Use pure Alpha-Beta search, find efficient general evaluation functions (e.g. learning as in AlphaZero).
  - Use UCT and enhance it with Minimax-based approaches (e.g., propagate Minimax values instead of averages within search tree, and/or use evaluation function instead of playouts with some probability) to bridge the gap between these approaches.

Web Sources

- Lots of additional information (e.g., GGP lecture slides, literature, basic players) collected at `http://www.general-game-playing.de`
- GGP Server online (originally developed at TU Dresden):
  - `http://ggpserver.general-game-playing.de`
  - Large number of game descriptions (currently more than 290)
  - Everyone can register
  - Possibility of self-play
  - Possibility to register player (and let it play)
  - Round-robin all the time
  - Often used in competitions

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