GENERIC HEURISTIC APPROACH TO GENERAL GAME PLAYING

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AGENDA

• Introduction to General Game Playing
• Game Description Language (GDL)
• A brief look at top GGP players
• Our approach – base idea
• Elements discovery
• Evaluation function construction
• Playing results
• Conclusions and future work
GARRY KASPAROV – DEEP BLUE [1997]
GENERAL GAME PLAYING (GGP)

Idea:

To create computer players (artificial intelligence programs) which are able to play a variety of games effectively.

- without human intervention
- even games never encountered before

GGP Competition:

- Tournament for GGP players started by Stanford Logic Group at Stanford University:
  http://games.stanford.edu/
- Natural, interactive, competitive platform for testing solutions
GENERAL GAME PLAYING

Motivation:

• Escape from heavy specialization
• Programs are expected to perform game analysis and learn how to play strongly
• Programmers develop intelligent mechanisms instead of ultra-fast algorithms dedicated to solve a particular game
• Follows the fundamental mission of AI better

• Possibility to incorporate various aspects of AI working in integrated fashion such as:
  - Knowledge representation
  - Abstract reasoning and decision making
  - Learning
  - Planning and evaluation
  - and more
GAME DESCRIPTION LANGUAGE (GDL)

No game specific knowledge should be encoded – players accept declarative description of games at **runtime**.

Game Description Language:

- Used to define complete rules of arbitrary games in GGP scenario
- Based on the first-order logic
- GDL derives from **Datalog**
- **Datalog** is a subset of **Prolog**

Logical rules as more compact representation than finite state machines (FSM)

- Power of games description is equivalent
- FSM representation is too complex e.g. Chess requires $10^{28}$ states
GAME DESCRIPTION LANGUAGE (GDL)

Available class of games (GDL-I):

- Finite
- Deterministic
- Synchronous

Available class of games (GDL-II):

- Finite
- Synchronous

How all this work:

- Logical rules enable to dynamically compute game states and aspects. Computed (realized) rule produces set of true facts.
- Like in Prolog, the whole world is defined by facts which are true.
- Predefined keywords are „entry points” to particular elements of the game flow
- There also exist constant facts which are always true
GDL

Keywords:
• role(r)
• init(p)
• true(p)
• does(r, a)
• next(p)
• goal(r, v ∈ [0..100])
• terminal
• distinct (v, w)
(role xplayer) (role oplayer)
(init (cell 1 1 b))
(init (cell 1 2 b))
...
(init (cell 3 3 b))
(init (control xplayer))

(<= (next (cell ?m ?n x))
    (does xplayer (mark ?m ?n))
    (true (cell ?m ?n b)))

(<= (next (cell ?m ?n b))
    (does ?w (mark ?j ?k))
    (true (cell ?m ?n b))
    (or (distinct ?m ?j) (distinct ?n ?k)))
...

(<= (legal white (mark ?x ?y))
    (true (cell ?x ?y b)))
(<= (legal black (mark ?x ?y))
    (true (cell ?x ?y b)))
...

(<= (row ?m ?x)
    (true (cell ?m 1 ?x))
    (true (cell ?m 2 ?x))
    (true (cell ?m 3 ?x)))
...

(<= (line ?x) (row ?m ?x))
(<= (line ?x) (column ?m ?x))
(<= (line ?x) (diagonal ?x))
(<= open (true (cell ?m ?n b)))
...

(<= (goal xplayer 100)
    (line x))
(<= (goal xplayer 50)
    (not (line x))
    (not (line o))
    (not open))

(<= (goal xplayer 0)
    (line o))
(<= (goal oplayer 100)
    (line o))
...

(<= terminal (line x))
(<= terminal (line o))
(<= terminal (not open))
A BRIEF LOOK AT OTHER GGP PLAYERS

Solutions based on a Min-max tree-search:

- ClunePlayer – *simple game model (payoff, mobility, termination, p stability, t stability)*
- FluxPlayer – *syntactic structures, fuzzy logic*
- ...

Solutions based on MonteCarlo simulations with UCT rule:

- CadiaPlayer
- Ary
- ...

*UCT rule – Upper Confidence Bounds Applied for Trees – balance between exploration and exploitation ratio*

Other:

- NEAT – Neuroevolution of Augmenting Topologies
Variant of UCB

When still within tree:

- Select each action once and from now on:
- Choose action-state pair that maximizes:

$$a^* = \arg\max_{a \in A(s)} \left[ Q(s,a) + C \sqrt{\frac{\ln N(s)}{N(s,a)}} \right]$$

a – action; s - state
Q(s,a) – the average return so far
N(s) – the number of visits to s
N(s,a) – the number of a selections in state s
IDEA

Let us distinguish objects build upon three types of GDL constructions:

• Table Rows (TR)
• Column Symbols (CS)
• Dynamic Symbols (DS)

Suplementary vocabulary:

• Row - (cell 1 1 b),..., (control xplayer)
• Table - cell, control
• Column – cell[0], cell[1], cell[2], control[0]
• Symbol – 1, 2, 3, b, x, xplayer

(cell 1 1 b)
(cell 1 2 b)
(cell 1 3 b)
(cell 2 2 x)
....
(control xplayer)
....
DISCOVERY PHASE - 1

Discovery of Table Rows (TR) and Column Symbols (CS)

- A few (3-4) parallel *random* simulations until only one is unfinished
- Synchronized with each other – common time steps

- During each time step: *TR* and *CS* are *counted*

and the quantities are subsequently compared among themselves in different simulations

The aim is to discover which TR and CS quantities vary:

- not as a result of only time step counter advancement
- as a result of performed action
DISCOVERY PHASE - 1

Simulation 1  Simulation 2  Simulation 3

count  compare  count  compare  count

quantity comparison at the same step
Here, Dynamic Symbols, are selected.

- Dynamic Symbols - symbols which change symbols they appear with in rows most significantly

- One complete random simulation

- After each performed action: two one-move look-aheads.
  - Set of rows with particular candidate DS in state after i-th: action: $S_i$
  - after the first look-ahead: $S_{(i+1)}$
  - after the second look-ahead: $S_{(i+1)'}$

Measure of dynamism: $val = 1 - \frac{2 \times |S_{(i+1)} \cap S_{(i+1)'|}}{|S_{(i+1)}| + |S_{(i+1)'}|}$
No more than one Dynamic Symbol per step is discovered

- Many have the same dynamism value => select at random
- The most varying has been already selected => no further action

Heuristic interpretation of a change of elements occurrences:

- **Table Rows:**
  a novel type of state/relation has occurred (e.g. check in chess)

- **Column Symbols:**
  probably some game-specific object (piece, stone, marker...) was created or destroyed

- **Dynamic Symbols:**
  property of game-specific object has been changed (e.g. position)
EVALUATION FUNCTION CONSTRUCTION

Performed during the learning phase before game starts

• play as many random simulations as possible

During each state of \(i\text{-th}\) simulation:

• Count occurrences of the discovered elements:
  
  - Table Rows \( ; \ TR[\text{table}_\text{name}] = \ldots \)
  - Column Symbols \( ; \ CS[\text{table}_\text{name}][\text{column}_\text{index}][\text{symbol}] = \ldots \)
  - Rows containing Dynamic Symbols \( ; \ DS_R[\text{table}_\text{name}][\text{symbol}] = \ldots \)

• Compute average value \(AVG_i\) for each element respectively
EVALUATION FUNCTION CONSTRUCTION

If game result is SUCCESS

- Add $AVG_i$ value to $WIN\_AVG\_TOTAL$

Else

- Add $AVG_i$ value to $LOSS\_AVG\_TOTAL$

$[WIN/LOSS]\_AVG\_TOTAL$ stores average values for won and lost games respectively.

This values are again averaged i.e.

$$AVG_W = \frac{\sum_{i \in WIN}(AVG_i)}{|WIN|} \quad , \quad AVG_L = \frac{\sum_{i \in LOSS}(AVG_i)}{|LOSS|}$$

For each heuristic object (bucket for counted occurrences):

- $weight = C \times \frac{AVG_W - AVG_L}{MaxValue}$

  - $C = 1.0$ for TR, CS
  - $C = 0.2$ for rows with DS
THE PLAYER

Heuristic function:
Linear combination of weights and number of occurrences of particular elements in a game state.

• take a state and compute its approximate strength evaluation

The function may be used:

• to gradually build a game using Iterative-Deepening DFS

• to guide Monte Carlo simulations
• to terminate MC simulation earlier
• for initial sorting of possible action-state pairs
RESULTS

Tests against reference player using MonteCarlo simulations with UCT

Variety of games:

- classic 2-player board games: chess, checkers, othello, sheep and wolf
- economic 3-player, simultaneous moves game: farmers
- match games: tic-tac-toe, connect four
- path-finding games: breakthrough, wallmaze

Various times for preparation and move

- T – unit proportional to an average simulation length [in seconds] for a particular game
## RESULTS

<table>
<thead>
<tr>
<th>Game</th>
<th>Heuristic Player vs UCT Clocks = [16T, 2T]</th>
<th>Heuristic Player vs UCT Clocks = [32T, 4T]</th>
<th>Heuristic Player vs UCT Clocks = [64T, 8T]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bomberman **</td>
<td>6% - 94%</td>
<td>11% - 86%</td>
<td>21% - 70%</td>
</tr>
<tr>
<td>Breakthrough **</td>
<td>50% - 50%</td>
<td>50% - 50%</td>
<td>48% - 52%</td>
</tr>
<tr>
<td>Checkers *</td>
<td>64% - 22%</td>
<td>66% - 20%</td>
<td>84% - 10%</td>
</tr>
<tr>
<td>Chess *</td>
<td>14% - 0%</td>
<td>35% - 10%</td>
<td>45% - 9%</td>
</tr>
<tr>
<td>Connectfour</td>
<td>48% - 40%</td>
<td>45% - 44%</td>
<td>45% - 46%</td>
</tr>
<tr>
<td>Farmers</td>
<td>36% - 64%</td>
<td>32% - 68%</td>
<td>14% - 86%</td>
</tr>
<tr>
<td>Othello</td>
<td>50% - 25%</td>
<td>29% - 49%</td>
<td>38% - 49%</td>
</tr>
<tr>
<td>Pacman *</td>
<td>78% - 22%</td>
<td>75% - 25%</td>
<td>55% - 45%</td>
</tr>
<tr>
<td>Tic-Tac-Toe</td>
<td>55% - 25%</td>
<td>30% - 33%</td>
<td>44% - 46%</td>
</tr>
<tr>
<td>Sheep and Wolf *</td>
<td>89% - 11%</td>
<td>76% - 24%</td>
<td>70% - 30%</td>
</tr>
<tr>
<td>Wallmaze *</td>
<td>3% - 0%</td>
<td>6% - 0%</td>
<td>29% - 25%</td>
</tr>
</tbody>
</table>
RESULTS

In most games, simple changes in global state are detected such as:

- Change in number of particular **pieces**:
  - in chess, checkers, othello, breakthrough, sheep and wolf
  - and their estimate influence on game
  - e.g. king twice as strong than a regular piece in checkers
  - e.g queen five times stronger than pawn in chess

- **Check** event in chess

- In farmers: **money, buildings and resources**

- Some board positions like (2,2) in Tic-Tac-Toe are detected as rows with dynamics symbols
CONCLUSIONS

• Winning ratio heavily depends on type of the game
• Positive influence on playing => there is hope
• Better results in slower times => need for better/longer learning procedure

• Evaluation function in significant way changes player’s strength
  ▪ either positively (if accurate) or negatively (because of overhead or facing wrong objectives)
CONCLUSIONS

Function may be used in various scenarios:

- With MIN-MAX like search
- With MonteCarlo UCT search
- As a main strategy or just search enhancement

- Computational time plays an important role in GGP
- Promising results but inability to discover complex correlations
- GDL lexical description is very difficult to work with
- Method of evaluation function construction might be dependent on type of game
- Still plenty of room for optimizations
CURRENT AND FUTURE WORK

System aimed at GGP Competition:

- Merging various playing strategies
- Dynamic selection and evaluation of available strategies
- Deeper analysis of game rules
- More informed „quasi-blind” search during Monte Carlo Simulations
- Faster logical reasoning

Future work:

- Towards cognitive human-like playing
- Visualization and search for patterns
ANY QUESTIONS?
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