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 inteligence 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/

- Held annually since 2005 *(at AAAI National Conference 2005-2010, IJCAI – 2011)*
- 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 – ***syntatic structures, fuzzy logic***
- ...

Solutions based on MonteCarlo simulations with UCT rule:

- CadiaPlayer
- Ary
- …

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

Other:

- NEAT – Neuroevolution of Augmenting Topologies

UCT RULE

Variant of UCB

When still within tree:

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

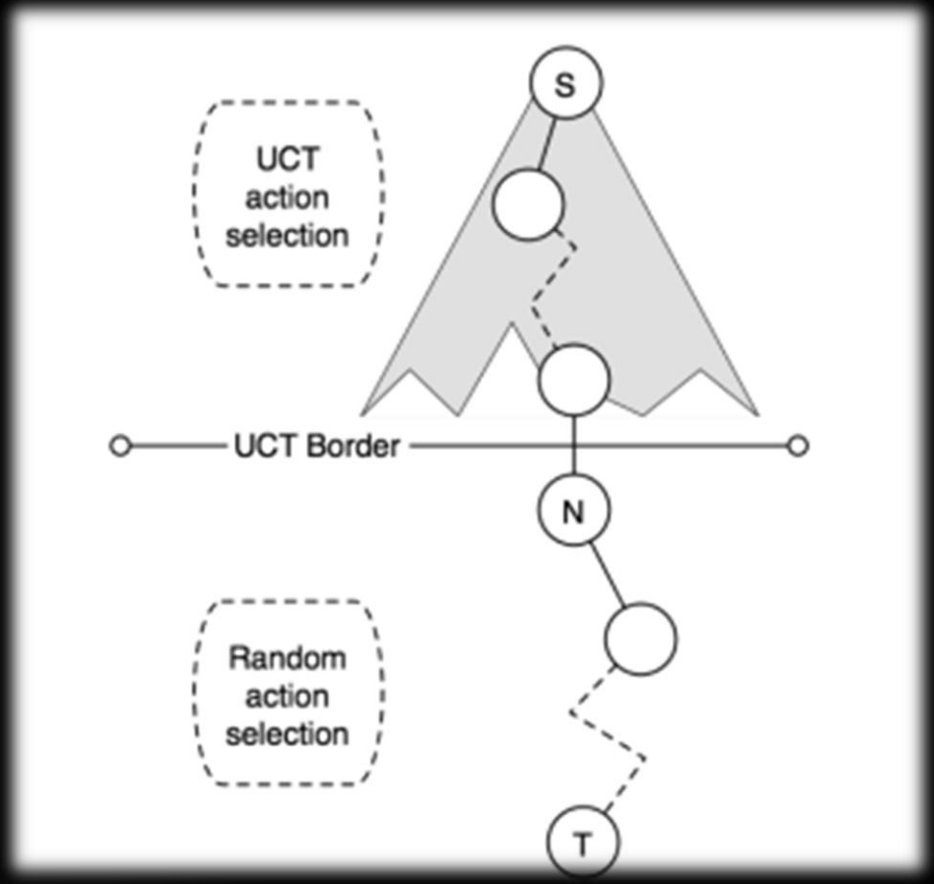
$$a^* = \arg\max_{a \in A(s)} \left\{ Q(s,a) + C \sqrt{\frac{\ln N(s)}{N(s,a)}} \right\}$$

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

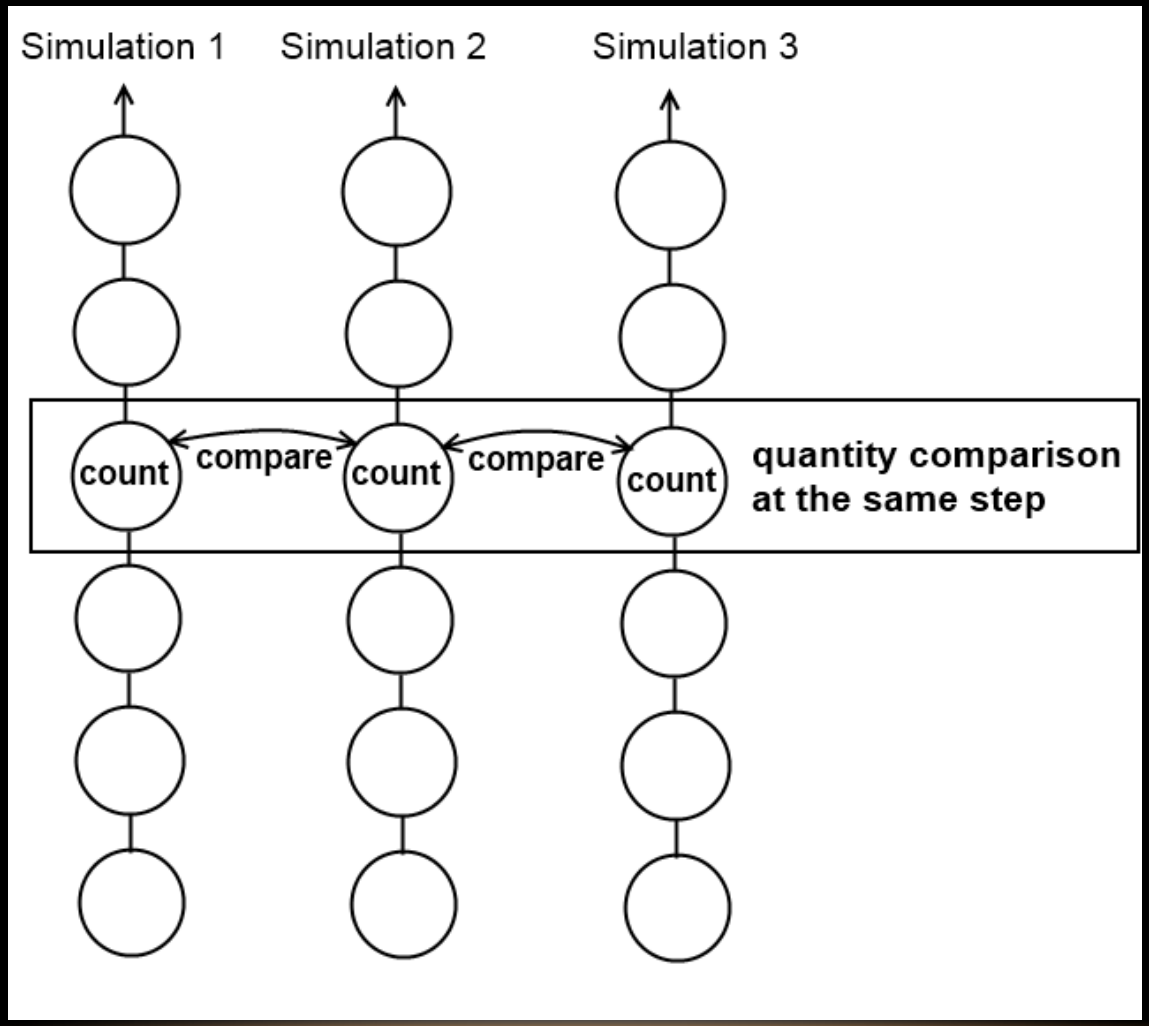
- During each time step: **TR** and **CS** are **counted**

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



DISCOVERY PHASE - 2

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: $$val = 1 - \frac{2*|S_{(i+1)} \cap S_{(i+1)'}|}{|S_{(i+1)}| + |S_{(i+1)'}|}$$

DISCOVERY PHASE - 2

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 occurences:

- **Table Rows**:

  a novel type of state/relation has occured (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-th*** simulation:

- Count occurences of the discovered elements:
  - ❑ Table Rows ; TR[table_name] = ...
  - ❑ Column Symbols ; CS[table_name][column_index][symbol] = ...
  - ❑ Rows containing Dynamic Symbols ; DS_R[table_name][symbol] = ...

- 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 occurences):

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

C = 1.0 for TR, CS

C = 0.2 for rows with DS

THE PLAYER

Heuristic function:

Linear combination of weights and number of occurences 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

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

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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