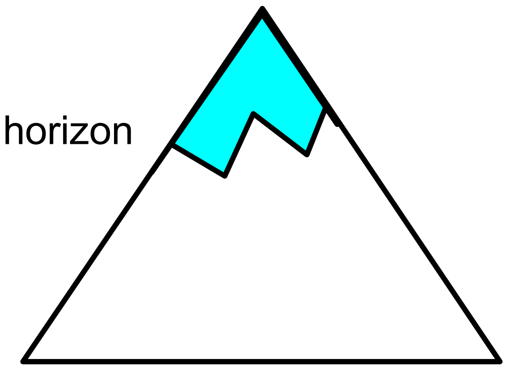
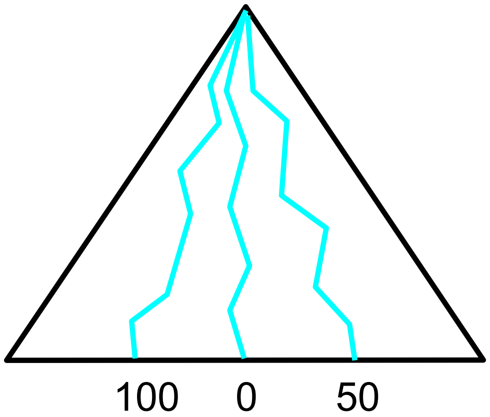
Outline

- Stochastic Search (blind general game playing)
- Heuristics Generation (informed general game playing)

Monte Carlo Tree Search (1)



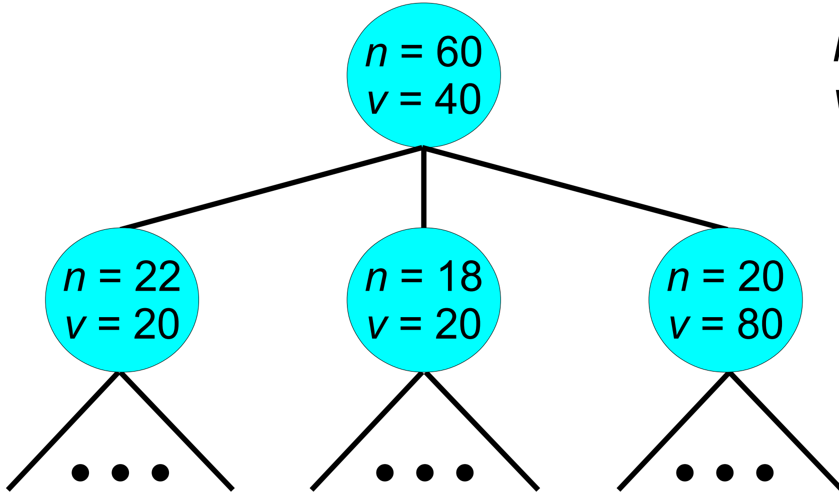
Game Tree Seach



MC Tree Search

Monte Carlo Tree Search (2)

Value of move = Average score returned by simulation



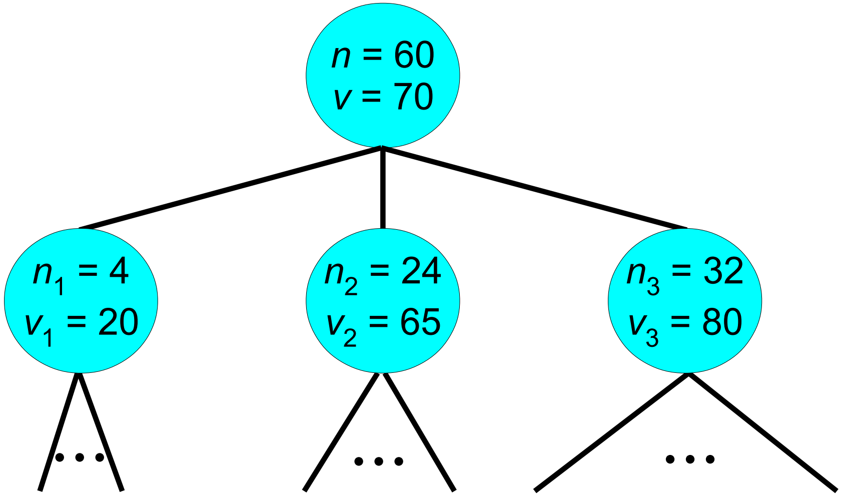
n = # of sample runs
v = average score

Confidence Bounds

- Play one random game for each move
- For next simulation choose move

$$argmax_i\left(v_i + C * \sqrt{\frac{\log n}{n_i}}\right)$$

confidence bound



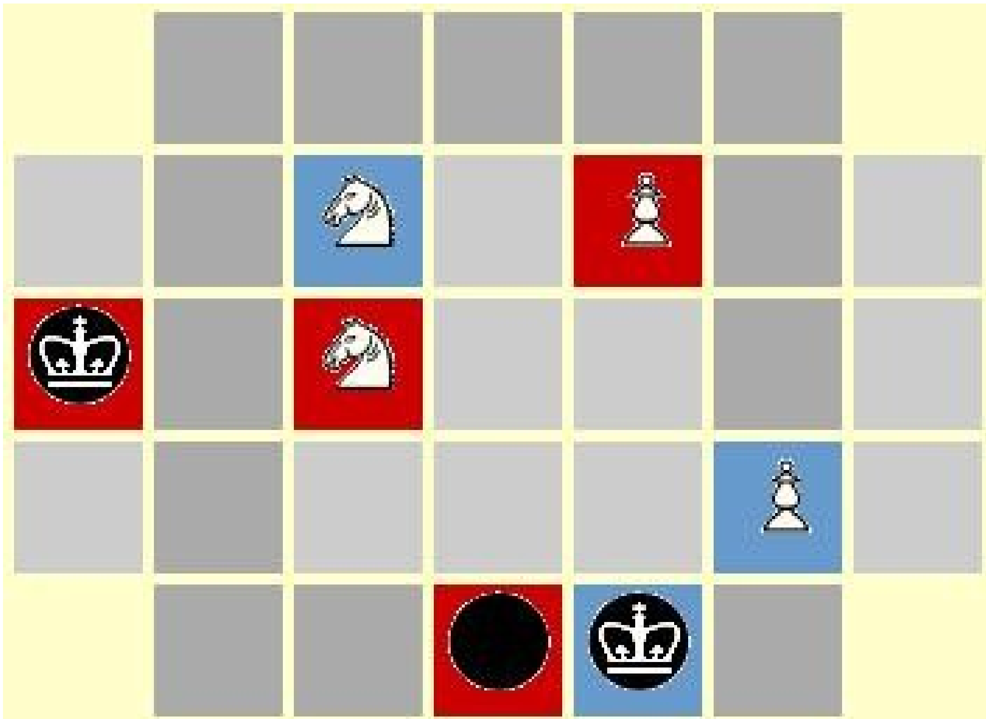
Assessment

Monte Carlo Tree Search works particularly well for games that

- converge to the goal
- reward greedy behaviour
- have a large branching factor
- do not admit a good heuristics

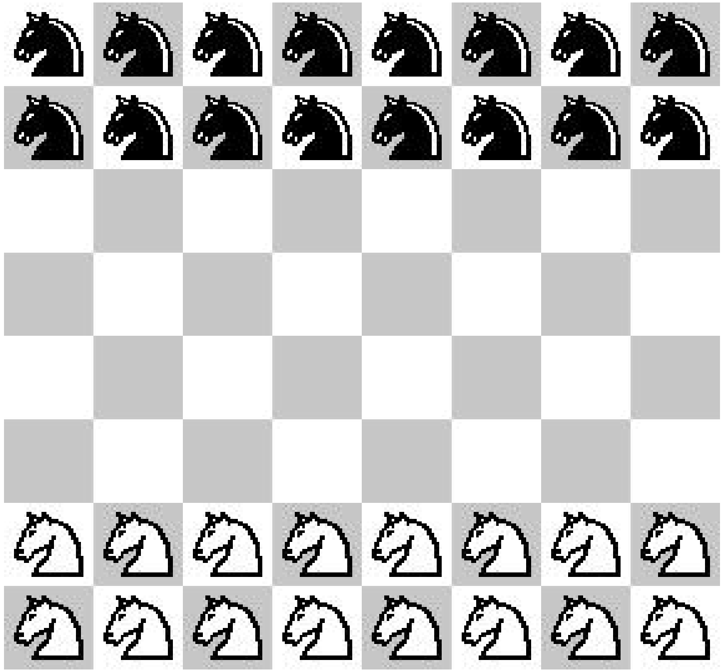
Also, MCT Search is the most successful method for Computer Go to date!

Example: Game Without a Good Heuristics



2pttcc4 – a random combination of Chess, Tic-Tac-Toe, Connect4

Example: Game Where Simple MCT Search Fails



`knightbreakthrough`

Informed Search: Exploiting Symmetries

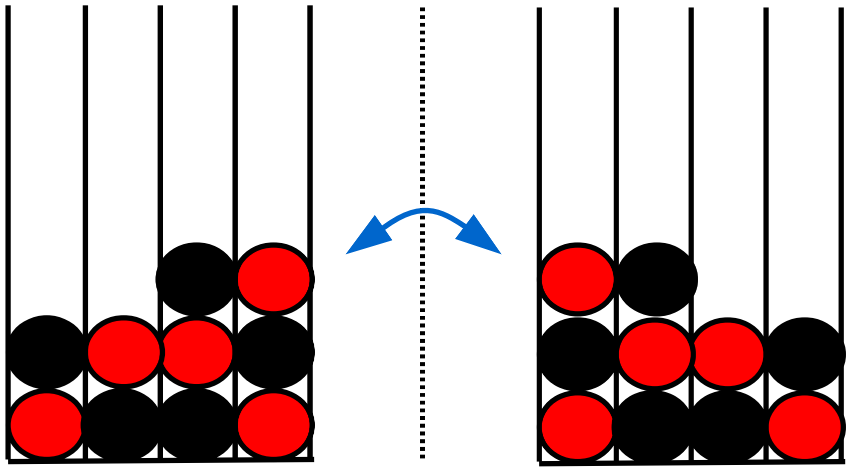
Symmetries can be logically derived from the rules of a game.

A symmetry relation over the elements of a domain is an equivalence relation such that

- two symmetric states are either both terminal or non-terminal
- if they are terminal, they have the same goal value
- if they are non-terminal, the legal moves in each of them are symmetric and yield symmetric states

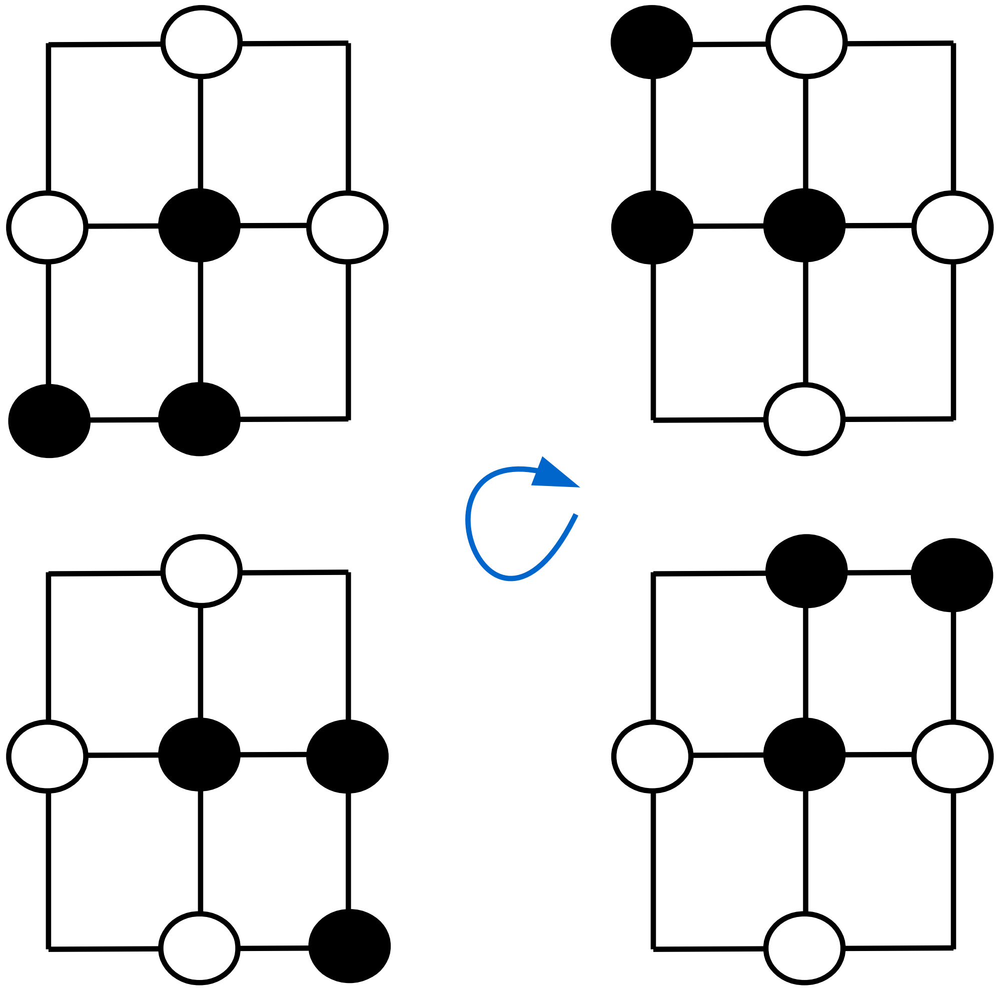
Example: Individual pebbles in Othello or Go

Reflectional Symmetry



Connect-3

Rotational Symmetry

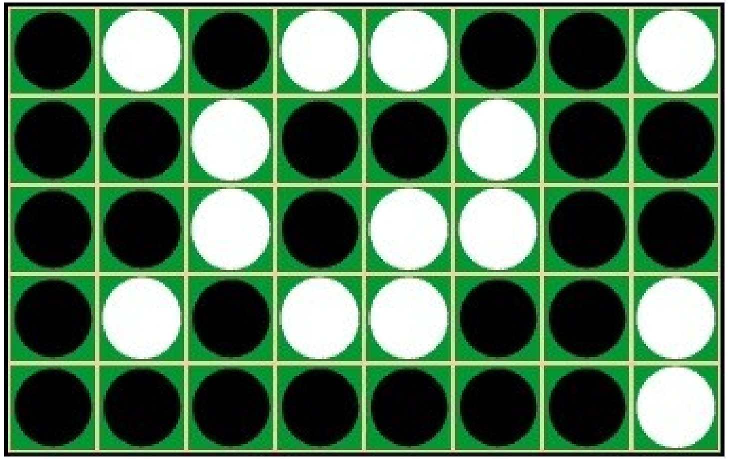


Capture Go

Informed Search: Factoring

hodgepodge = Chess + Othello

Branching factor: a



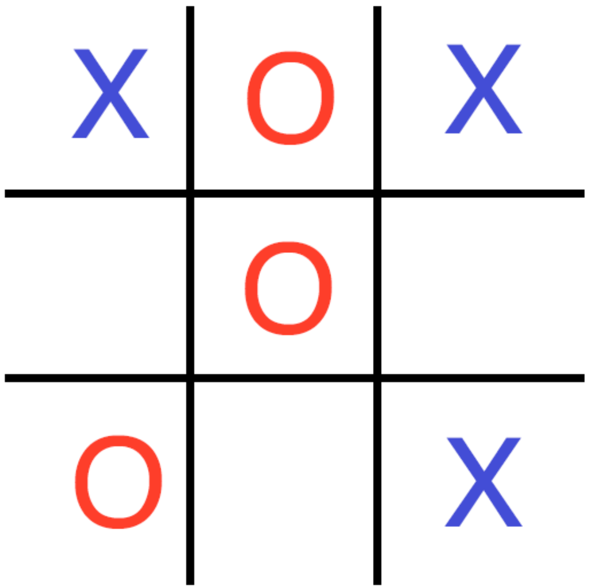
Branching factor: b

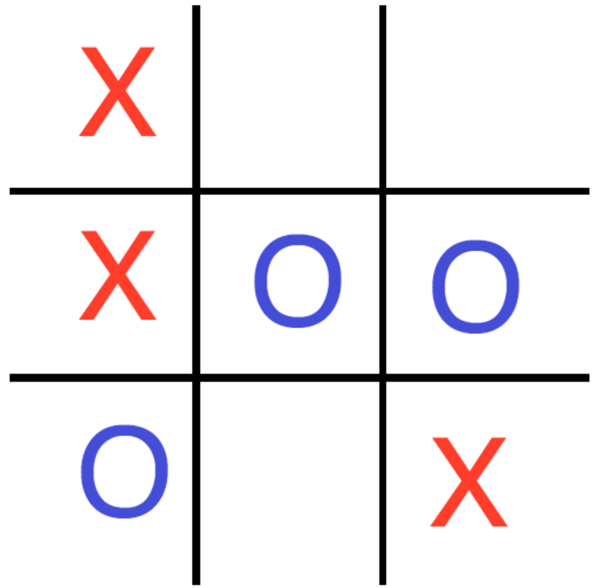
Branching factor as given to players: $a * b$

Fringe of tree at depth n as given: $(a * b)^n$

Fringe of tree at depth n factored: $a^n + b^n$

Double Noughts And Crosses





Branching factor: 81, 64, 49, 36, 25, 16, 9, 4, 1

Branching factor (factored): 9, 8, 7, 6, 5, 4, 3, 2, 1 (times 2)

Game Factoring and its Use

1. Compute factors
   - Behavioural factoring
   - Goal factoring

2. Play factors

3. Reassemble solution
   - Append plans
   - Interleave plans
   - Parallelise plans with simultaneous actions

Factoring

A set $\mathscr{F}$ of features and moves is a *behavioural factor* if and only if there are no connections between the features and moves in $\mathscr{F}$ and those outside of $\mathscr{F}$.

Goal factoring (the simple case): goal is a conjunction

- Partition conjuncts over behavioural factors
- Create new goals for each factor

Goal factoring (the complex case): goal is a disjunction of conjunctions

- Split each conjunct as above
- Check for lossless joins, i.e. when recombined, we get the same results

Good:

`(p1 ∧ q1) ∨ (p1 ∧ q2)`

Bad:

`(p1 ∧ q1) ∨ (p2 ∧ q2)`

Blind Search

- Blind search: only assign scores to nodes based on the evaluation of the complete subtrees at those nodes
- Problem: can relatively rarely see all the way to the bottom of the tree for a single node, even less so for every successor node
- Solution: improve efficiency of inference
- Solution: assign intermediate scores to nodes based on an evaluation function
- Metagaming means to reason about properties of games

Informed Search: Using Evaluation Functions

- Typically designed by programmers/humans
- A great deal of thought and empirical testing goes into choosing one or more good functions
- E.g.
  - piece count, piece values in chess
  - holding corners in Othello
- But this requires knowledge of the game's structure, semantics, play order, etc.

The General Case

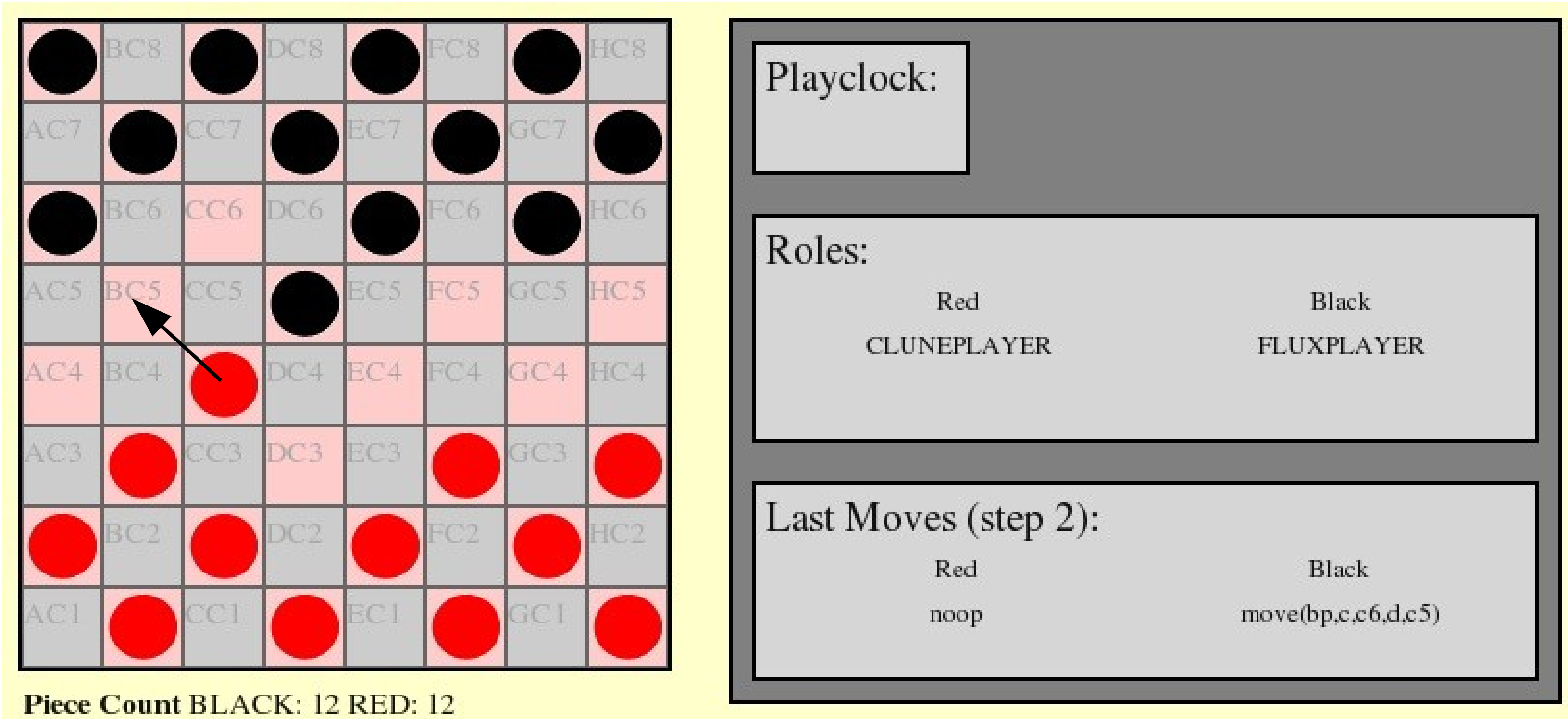
- No knowledge of features
- No insight into game structure
- No intuition about what is a good feature for this particular game

- Some general ideas work in many cases – but sometimes they don't ...
- E.g. mobility heuristics, novelty heuristics, goal distance

Mobility

- More moves means better state
  Optionally: limiting opponent moves is better too
- The good:
  In many games, being cornered or forced into making a move is quite bad
  - In Chess, when you are in check, you can do relatively few things compared to not being in check
  - In Othello, having few moves means you have little control of the board
- The bad: Mobility is counterproductive for Checkers

Worldcup 2006: Cluneplayer vs. Fluxplayer



Inverse Mobility

- Having fewer things to do is better
  Optionally: giving opponent things to do is better
- This works in some games, like Nothello, where you might in fact want to lose pieces
- How to decide between mobility and inverse mobility heuristics?

Novelty

- Changing the game state is better
- The good:
  - Changing things as much as possible can help avoid getting stuck
  - When it is unclear what to do, maybe the best thing is to throw in some directed randomness
- The bad:
  - Changing the game state can happen if you throw away your own pieces
  - Unclear if novelty per se actually goes anywhere useful for anybody

Identifying Structures: Relations

A successor relation is a binary relation that is antisymmetric, functional, and injective.

Example:

```
succ(1,2) ∧ succ(2,3) ∧ succ(3,4) ∧ ...
next(a,b) ∧ next(b,c) ∧ next(c,d) ∧ ...
```

An order relation is a binary relation that is antisymmetric and transitive.

Example:

```
lessthan(A,B) <= succ(A,B)
lessthan(A,C) <= succ(A,B) ∧ lessthan(B,C)
```

Boards and Pieces

An (*m*-dimensional) board is an *n*-ary state feature ($n \geq m+1$) with

- *m* arguments whose domains are successor relations
- 1 output argument

Example:

`cell(a,1,whiterook) ∧ cell(b,1,whiteknight) ∧ ...`

A marker is an element of the domain of a board's output argument.

A piece is a marker which is in at most one board cell at a time.

Example: Pebbles in Othello, White King in Chess

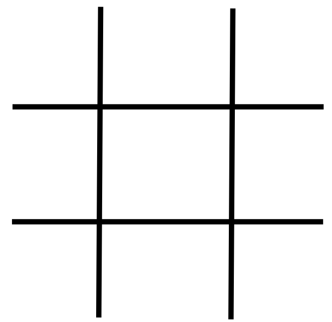
Simple Goal Distance

- The better an intermediate state satisfies the goal specification, the better it is
- Fuzzy Logic to evaluate the "degree of truth" of a goal formula
- Value $0.5 < p < 1.0$ for true literals (and $1-p$ for false literals)

Example: Noughts And Crosses

```
goal(xplayer,100) <= true(cell(M,1,x)) ∧
                     true(cell(M,2,x)) ∧
                     true(cell(M,3,x))
                     ∨
                     true(cell(1,N,x)) ∧
                     true(cell(2,N,x)) ∧
                     true(cell(3,N,x))
                     ∨
                     true(cell(1,1,x)) ∧
                     true(cell(2,2,x)) ∧
                     true(cell(3,3,x))
                     ∨
                     true(cell(1,3,x)) ∧
                     true(cell(2,2,x)) ∧
                     true(cell(3,1,x))
```

Evaluation of Intermediate States



fuzzy_eval(goal(xplayer,100)) after does(xplayer,mark(2,2))
> fuzzy_eval(goal(xplayer,100)) after does(xplayer,mark(1,1))
> fuzzy_eval(goal(xplayer,100)) after does(xplayer,mark(1,2))

Advanced Goal Distance

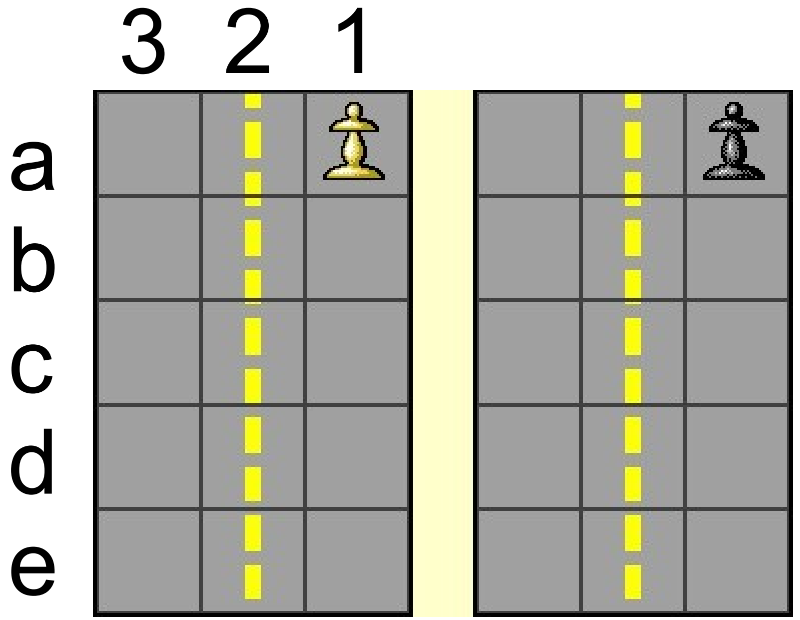
The closer the current value of a functional state feature to the target value, the "less false" is the corresponding goal literal

- Remember how successor relations and order relations can be identified
- These relations define metrics Δ on the values of a functional feature
- Truth degree of `true`(f(a)) given that `true`(f(b)):

$$(1-p)-(1-p)*\frac{\Delta(b,a)}{|dom(f)|}$$

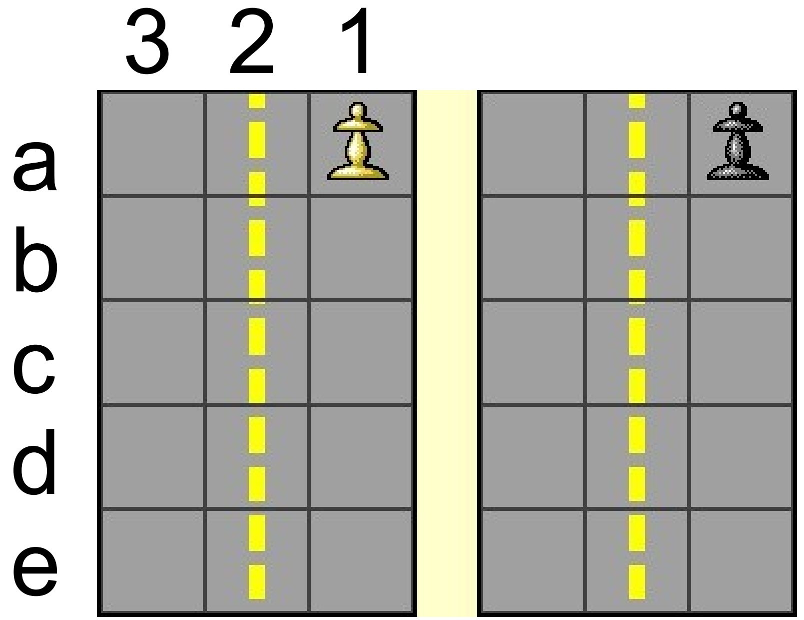
where (1-*p*) is the base value >0 assigned to false literals, as before

Example: The Goal in Racetrack




```
goal(white,100) <= true(lane(white,e))
init(lane(white,a))
```

Evaluation of Intermediate States

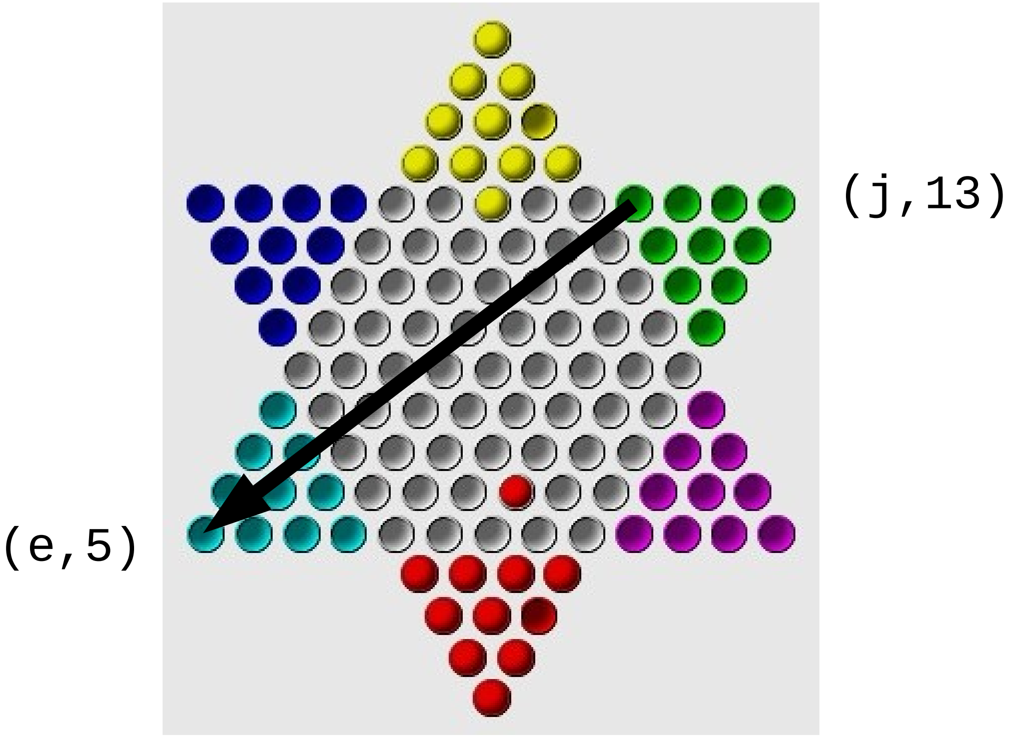


Δ(b,e) = 3 < Δ(a,e) = 4, hence:

fuzzy_eval(`goal(white,100)`) after `does(white,move(a,1,a,2))`

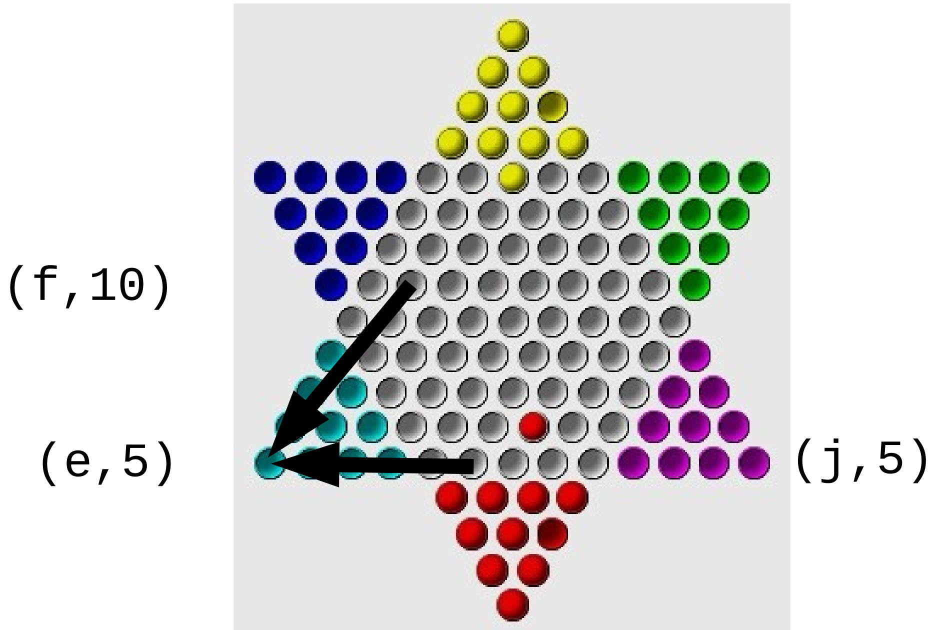
< fuzzy_eval(`goal(white,100)`) after `does(white,move(a,1,b,1))`

Another Example




```
init(cell(green,j,13)) ∧ ...
goal(green,100) <= true(cell(green,e,5)) ∧ ...
```

Chinese Checkers (cont'd)



$\Delta((j,5), (e,5)) = 5 < \Delta((f,10), (e,5)) = 6$

Assessment

Fuzzy goal evaluation works particularly well for games that

- have independent (conjunctive) sub-goals
  15-Puzzle
- converge to the goal
  Chinese Checkers
- have quantitative features
  Othello
- have partial goals
  Peg Jumping, Chinese Checkers with >2 players

Background Reading

Logic

- Russell & Norvig AIMA (3rd ed): Chapter 8 – Sections 8.1 and 8.2

Logic Programming

- Russell & Norvig AIMA (3rd ed): Chapter 9 – Sections 9.1, 9.2, and 9.4

Planning

- Russell & Norvig AIMA (3rd ed): Chapter 10 – Sections 10.1 and 10.2
  Chapter 11 – Section 11.3
  (2nd edition: 11.1, 11.2, 12.3)

General Game Playing

- `games.stanford.edu/competition/misc/aaai.pdf`
- `www.ru.is/faculty/hif/papers/cadiaplayer_aaai08.pdf`
- `cgi.cse.unsw.edu.au/~mit/Papers/AAAI07a.pdf`

Summary

- General Game Playing – an AI Grand Challenge
- Multiple AI methods come together
  Logic and Reasoning, Planning and Search, Learning
- For more information see
  `general-game-playing.de`
  `games.stanford.edu`
- Or ask `mit@cse.unsw.edu.au`