Algorithmic explorations in a Partial Information Game

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Agenda

- Partial Information Games
- Chess as a wargame: Kriegspiel
- Algorithmic issues in Kriegspiel
- Designing a Kriegspiel program
- Planning in Kriegspiel

Partial Information Games
(PIGs)

- PIGs are games in which players know only partially the game status
- Examples:
  - Card games, like Poker or Bridge
  - Board games, like Stratego or Risk
  - Wargames for military training
  - Some PIGs are Chess variants:
    eg. Kriegspiel, Dark Chess, others

Perfect vs. imperfect

- Perfect information games: all players know the full state of the game and see all the moves
  - Checkers, Chess, Go
- Imperfect information games: the players have partial and different knowledge about the state of the game, but see the moves
  - Poker, Stratego, Risk, Battleship
- Imperfect information games where also the moves are unknown ("*fog of war*"), hence a referee is necessary:
  - Kriegspiel, Phantom Go

Fog of war

- The **fog of war** is the uncertainty in situational awareness experienced by participants in military operations
- The term concerns uncertainty regarding one's own capability, adversary capability, and adversary intent
- Concept introduced by Carl von Clausewitz in his posthumously published book, *Vom Kriege* (1837)

(definition from Wikipedia)

Partial information is hard

- Zermelo's theorem: in a two-player zero-sum game of perfect information either player has an optimal strategy that guarantees a minimum payoff
- It is the foundation of the **Minimax** theorem, which is the basis of game tree search
- It does not hold in games with partial information (even if an optimal strategy exists, the player may not be allowed to see it)

Information set

Playing a PIG, an agent:

- Has to make some hypotheses - *beliefs* - about the state of the game (building an *information set*)
- Has to take decisions in uncertainty, possibly assigning some probabilities to the beliefs included in the information set

Poker and Bridge

- These are PIGs because players do not know other players' hands
- In Poker ignorance is symmetric
- In Bridge there is some asymmetry: Declarer plays both Dummy and his own cards, instead the other two players must cooperate "in the dark"

Stratego

- This is a PIG because the opponent pieces are covered

Risk (Risiko)

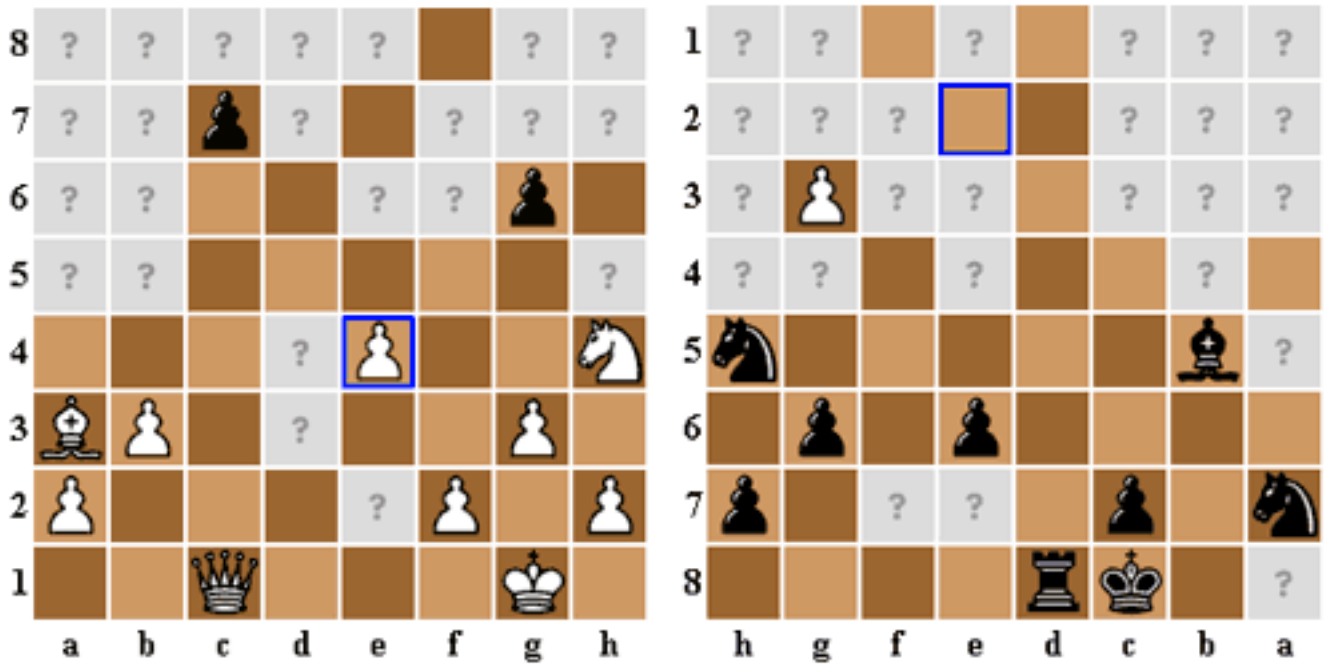
This is a PIG because the players' goals are secret

PIG based on Chess

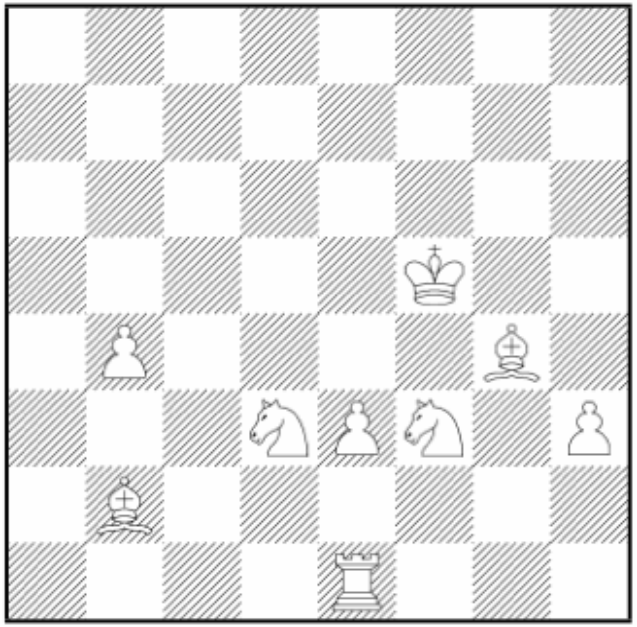
- Kriegspiel – invented in 1890
  - Referee: Eastern or Western rules
  - Derivatives (eg. Invisible Chess)
- Dark Chess
  - Asimmetric knowledge
  - Simmetric knowledge
- Stealth Chess, Cloack Chess

Stealth Chess

Dark Chess



Kriegspiel



Kriegspiel is a partial information variant of Chess (invented 1890)

Players do not see their opponent's pieces or moves

They hear some "outcome" of each move from a referee, similarly as in wargames

If a player tries to make an illegal move, he is allowed to try again

Kriegspiel

Gambit Club, London, 1946

Kriegspiel

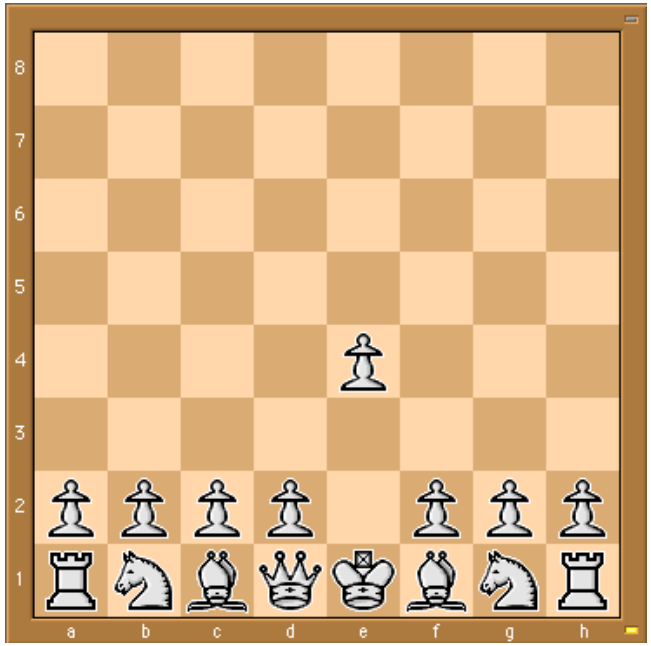
- Two players, all rules of normal Chess
- Each player only sees his army and moves
- A referee R sees the complete position and players' moves
- After a player P makes a move, R accepts it if legal (otherways P tries another move), and annunces captures and checks, if any

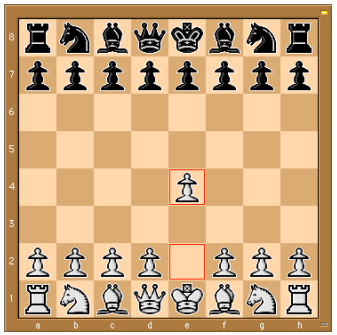
Referee's messages

- After each move by a player P, the referee R can
  - Say "illegal": the move is refused and player P tries another
  - Say "check": the move is accepted, the opponent's King is in check
  - Say "capture on square XY": the move is accepted, an opponent piece has been captured
  - Stay silent: the move is accepted and the other player is informed he has to move

Example

White vision after e4

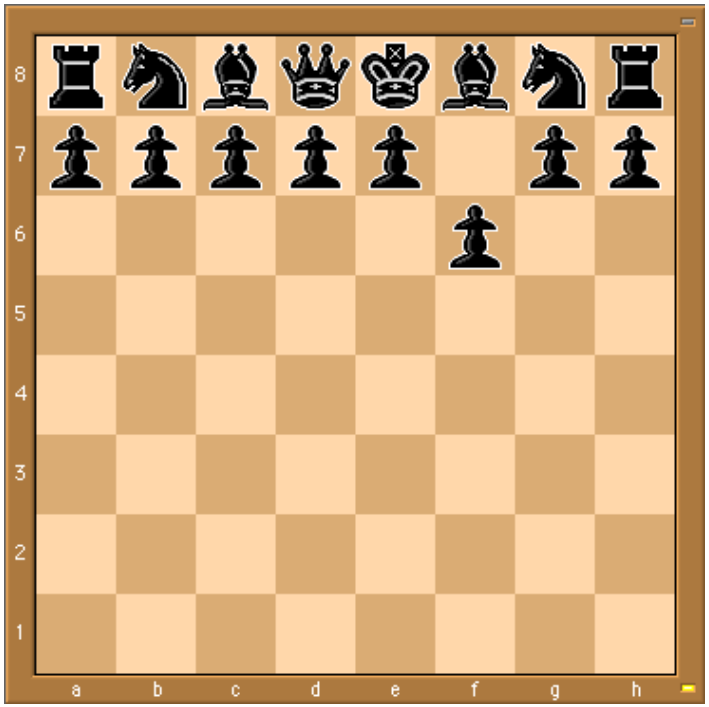


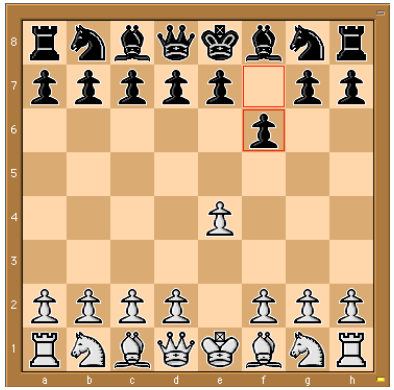


Referee: silent

Example

Black vision after f6

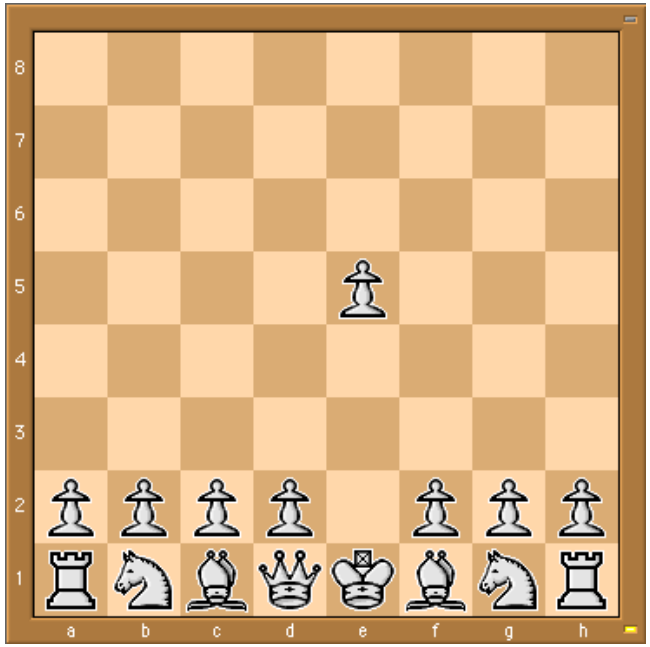


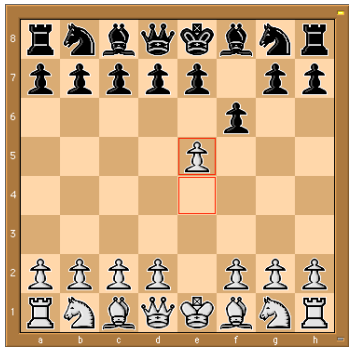


Referee: silent

Example

White vision after e5

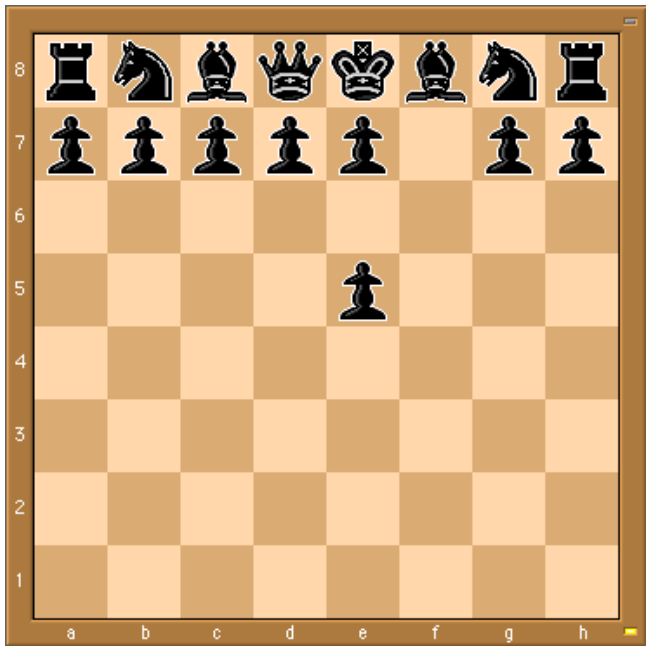


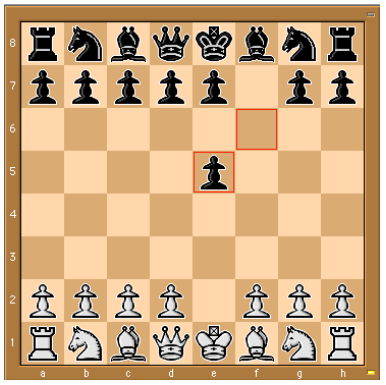


Referee: “one pawn try”

Example

Black vision after fxe5

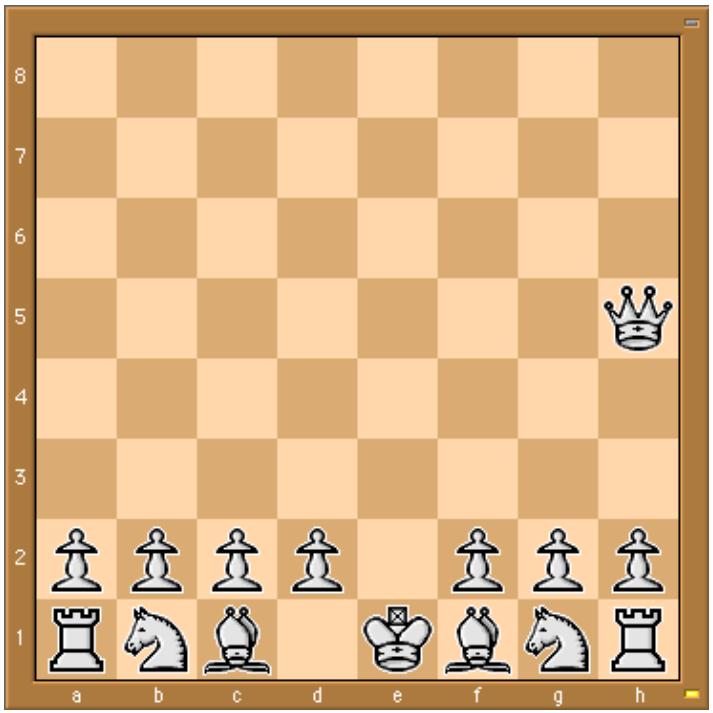




Referee: “pawn captured in e5”

Example

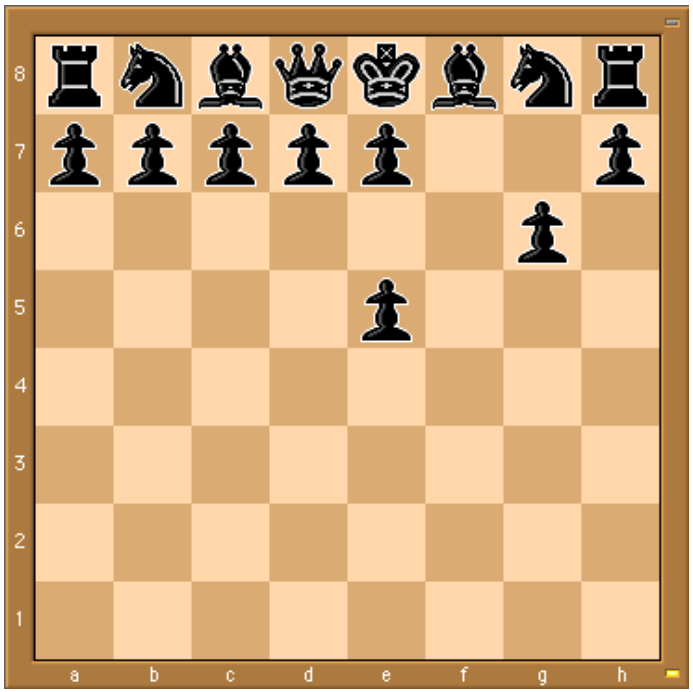
White vision after Qh5

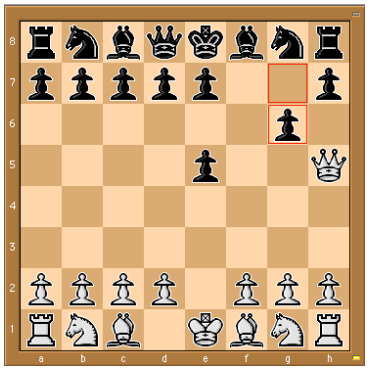


Referee: “check on short diagonal”

Example

Black vision after g6

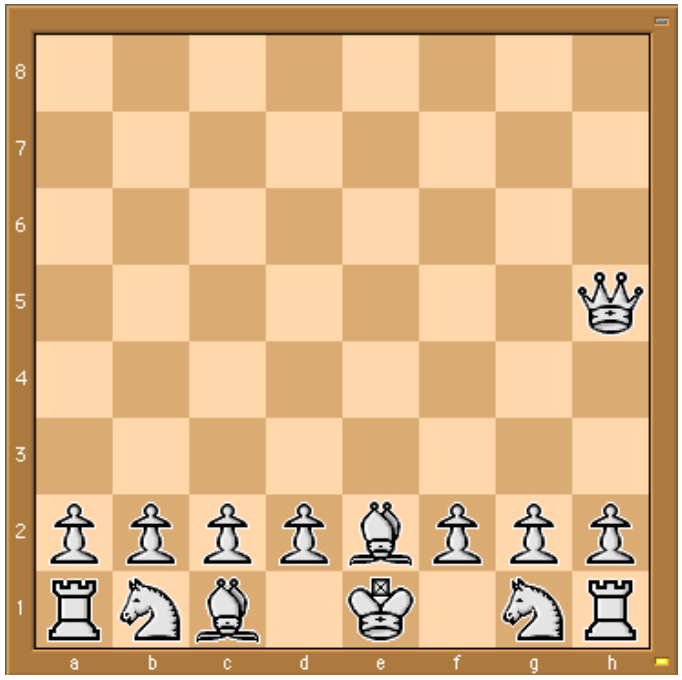


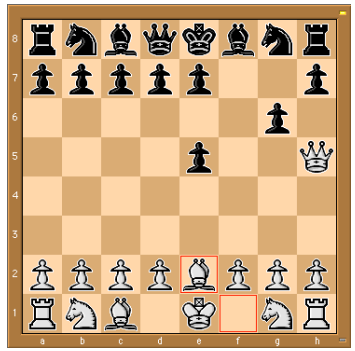


Referee: silent

Example

White vision after Be2

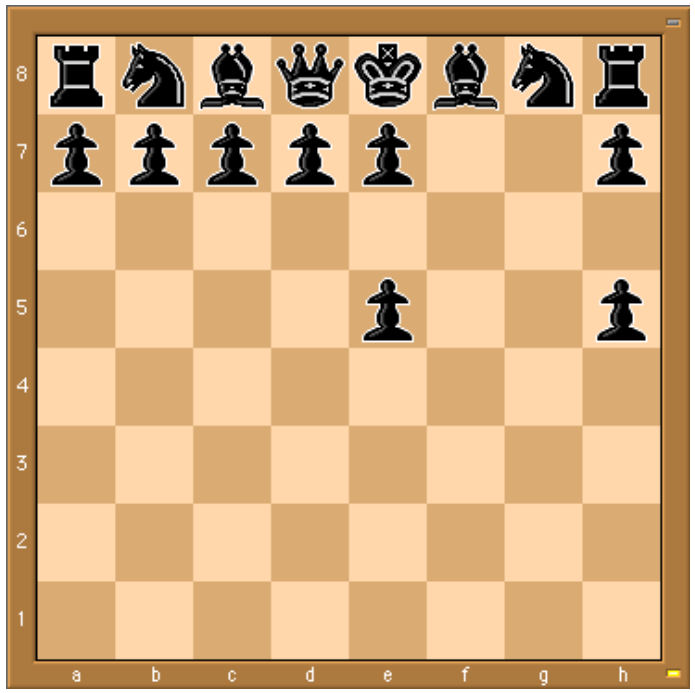


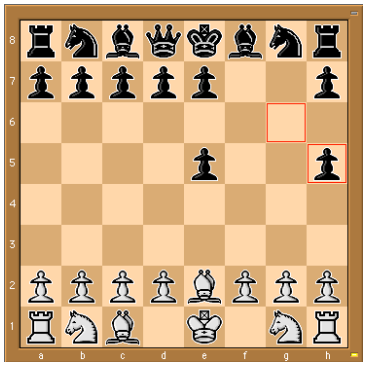


Referee: “one pawn try”

Example

Black vision after gxh5

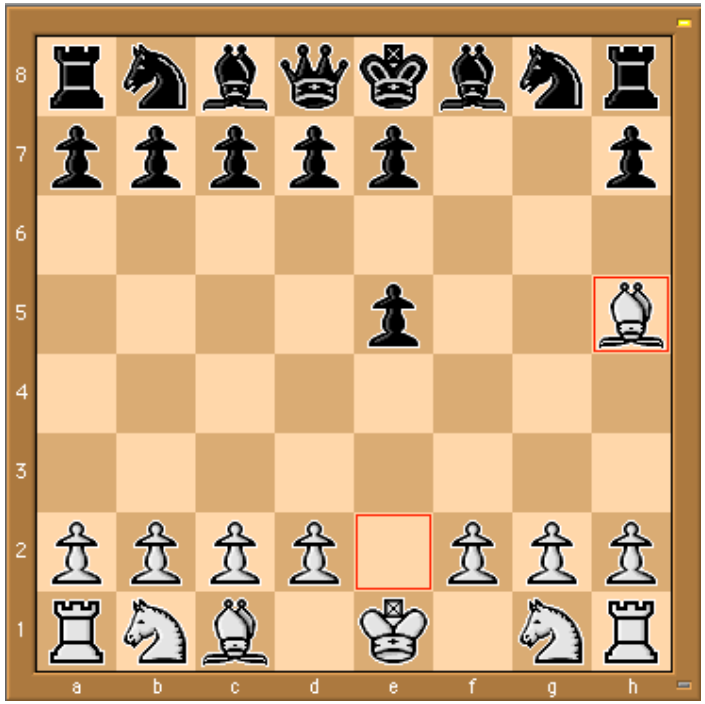




Referee: “piece captured in h5”

Example

White moves Bh5



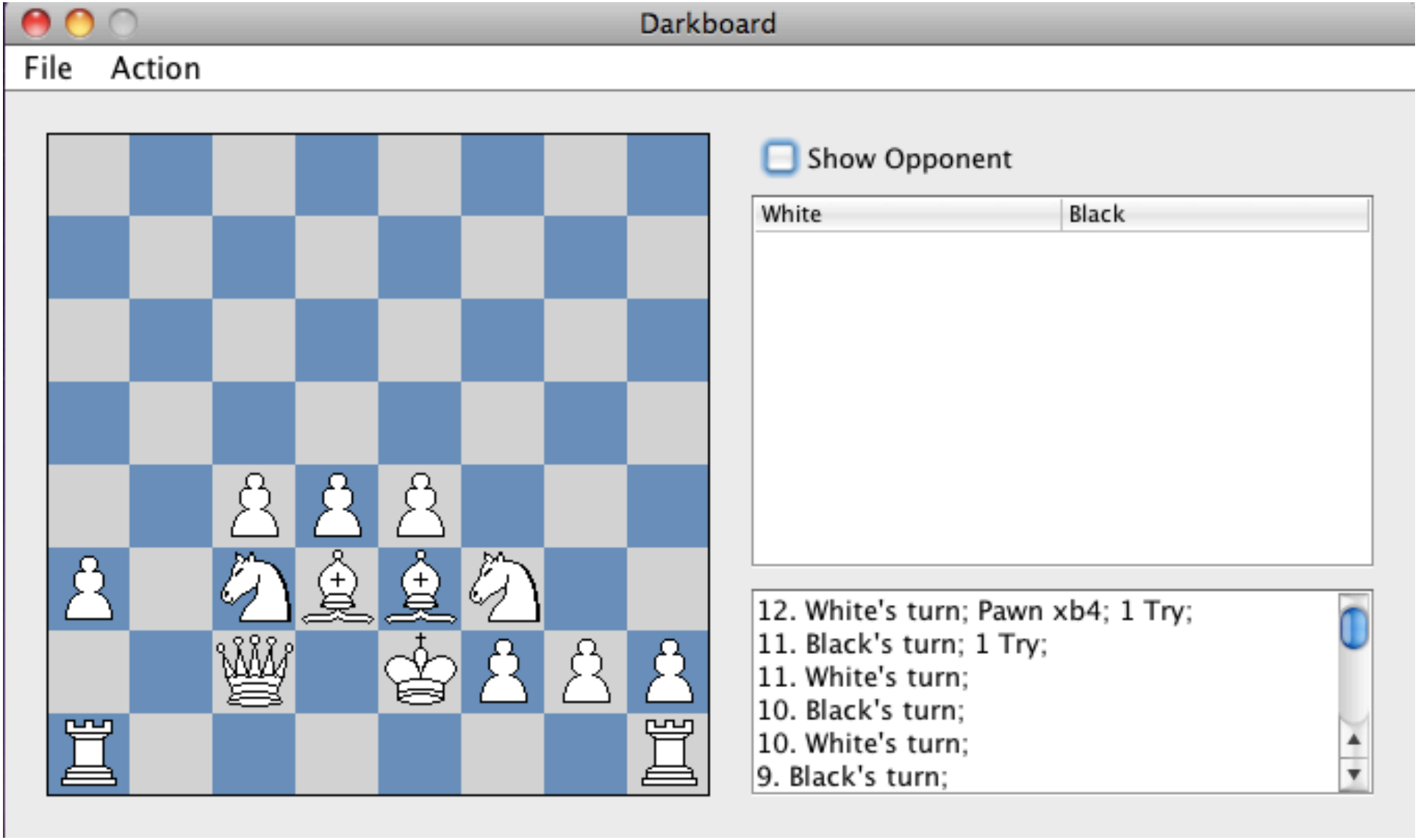
Referee:

“pawn captured in h5;

check on short diagonal;

checkmate”

An interface for Kriegspiel



Kriegspiel practice

- On Internet Chess Club it is Wild variant 16
- Hundreds of rated players
  - Some are strong chess players (GMs, etc.)
- About 50 games per day
- Some weak computer players
- World championship @ICGA olympics
- Simple applets: www.pathguy.com/chess/Kriegsp2.htm

Why do we study Kriegspiel?

- **Complex:** extremely large belief state makes an explicit representation of it computationally intractable
- **Challenging:** currently, the best humans are still far ahead of computer players at this game
- **Convenient:** same rules as Chess: this allows for reuse of a certain amount of game theory and software

Kriegspiel as a scientific problem

- Can the computational knowledge we have on Chess be applied on Kriegspiel?
- Is Kriegspiel better than Chess as a “Drosophila for AI”?
- Which problems are similar to Kriegspiel?

Kriegspiel and Game Theory

- Kriegspiel was invented to make Chess more similar to a wargame
- Studied by Von Neumann under the name of Blind Chess (in the book *Theory of Games and Economic Behavior*)
- Played by Nash and others researchers at RAND Corporation
- Papers by Shapley, Nau, Russell, and others

Algorithmic explorations

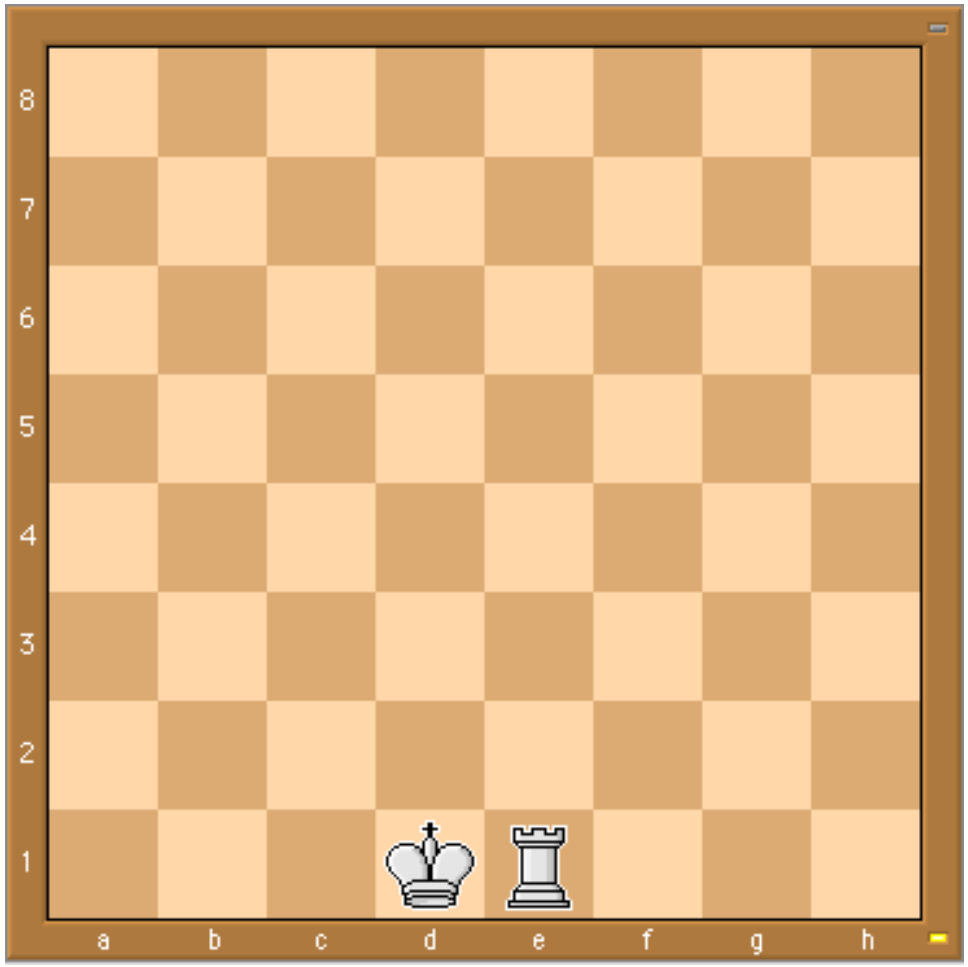
@UniBo we have developed for Kriegspiel:

- An extended minimax search
- A MonteCarlo Tree Search
- A retrograde algorithm to play some endgames perfectly
- A fully working program (Darkboard), world champion since 2006
- An experimental priority planner

Metapositions

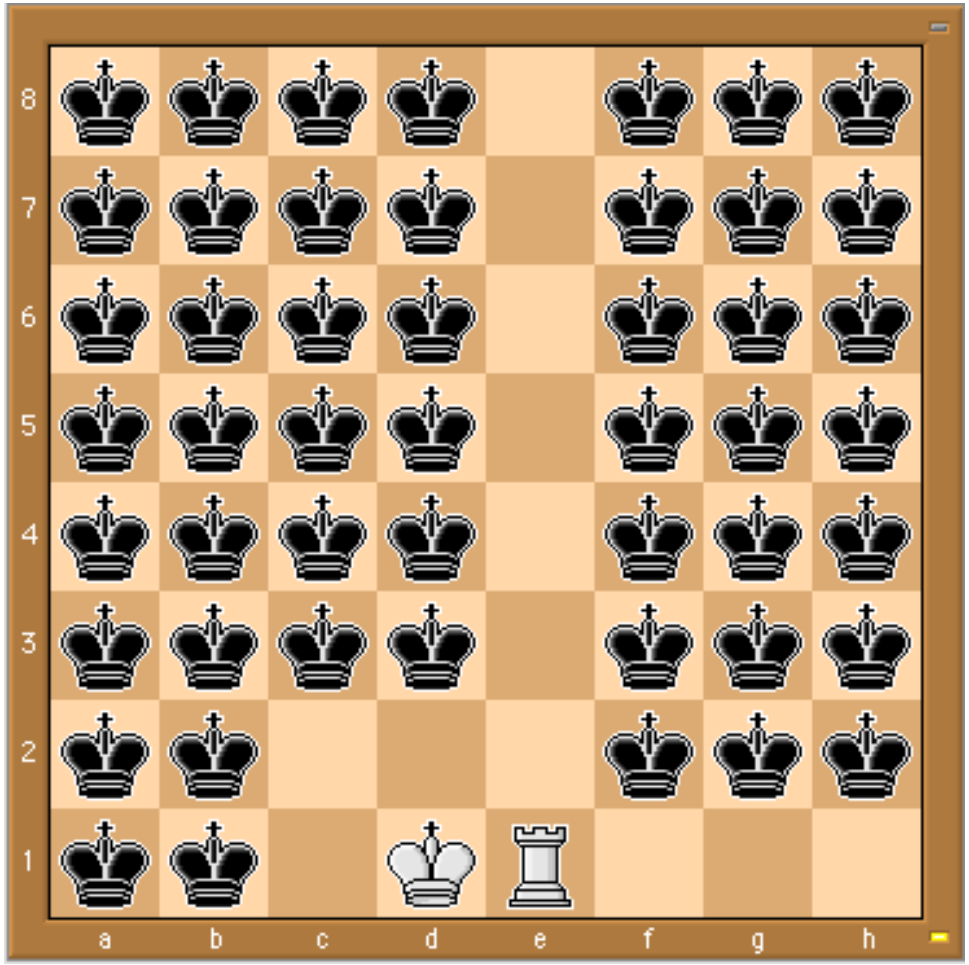
- Our first program played building a tree of metapositions
- A metaposition groups several game states together to provide the illusion of complete information
- The states with the same strategy space (set of moves available to the player) may be merged together and a game tree can be built
- Concept introduced in [Sakuta 2001] to deal with a Shogi equivalent of Kriegspiel, used to solve endgame positions

KR vs K in Kriegspiel



The Black King is alone, somewhere. Can White give checkmate?

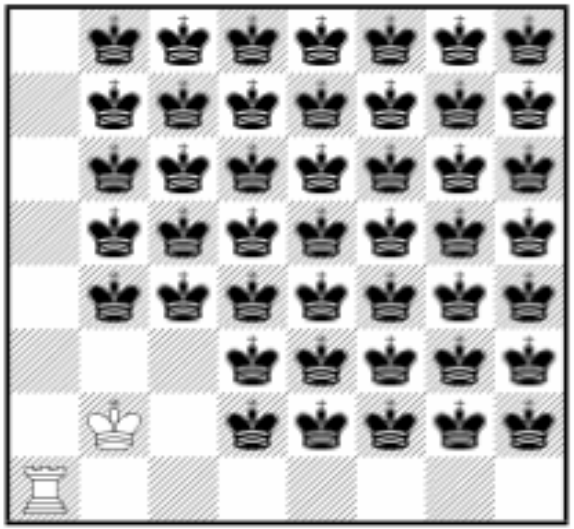
Metaposition



States as metapositions

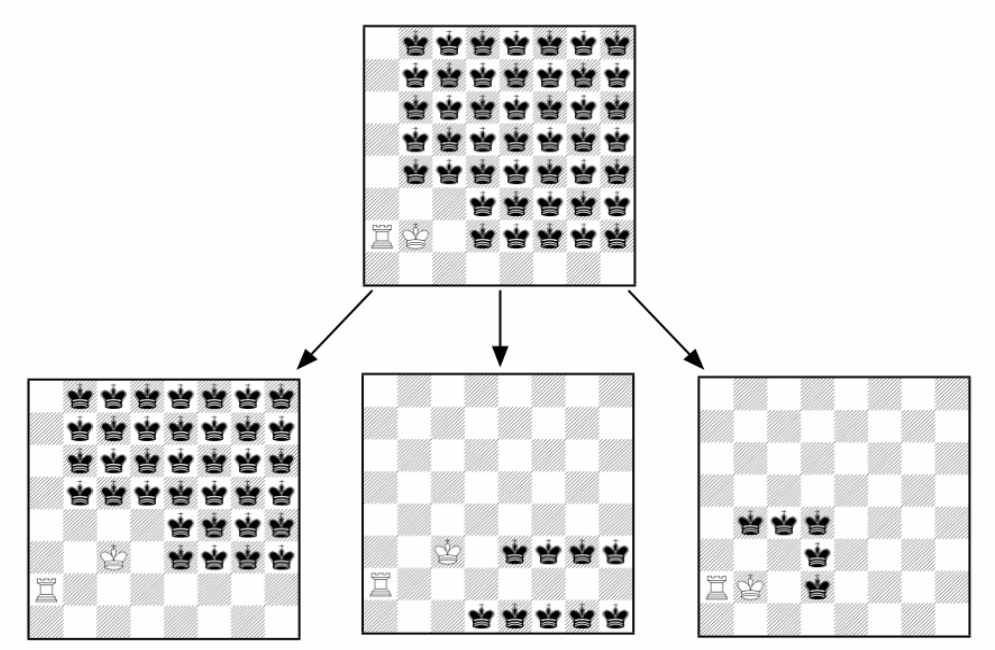
- **Belief state:** the set of states compatible with our observations so far
- Basic idea: we represent a belief state as a **metaposition**
- A metaposition groups several game states together to provide the illusion of perfect information
- **The goal is to apply a variant of minimax including the referee's messages**

What it looks like



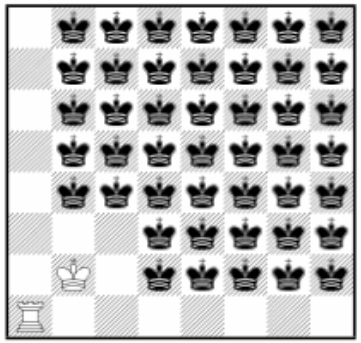
- Metapositions are simpler to represent if only the enemy king is left on the board.
- Example taken from a King and Rook vs. King endgame, White to move, maximum uncertainty

Updating metapositions



- White plays Kc3.
- In this example, Kc3 can be **silent**, **rank check** or **illegal**.
- The first two cases include Black's move (the enemy king spreads)

Metaposition evaluation



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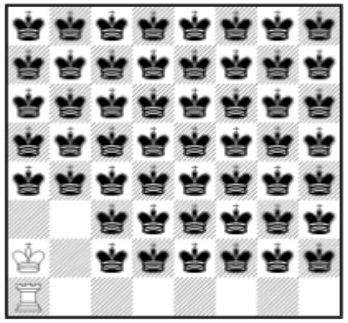
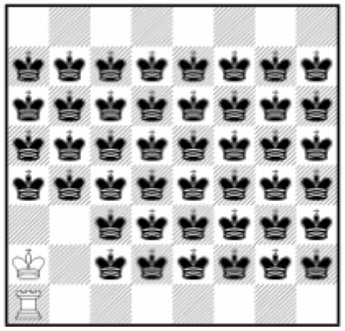
- We developed an evaluation function to decorate minimax trees, as in chess
- The algorithm will choose the child with the highest value (MAX)
- If the opponent is omniscient, it will pick the referee's message with the lowest value (MIN)

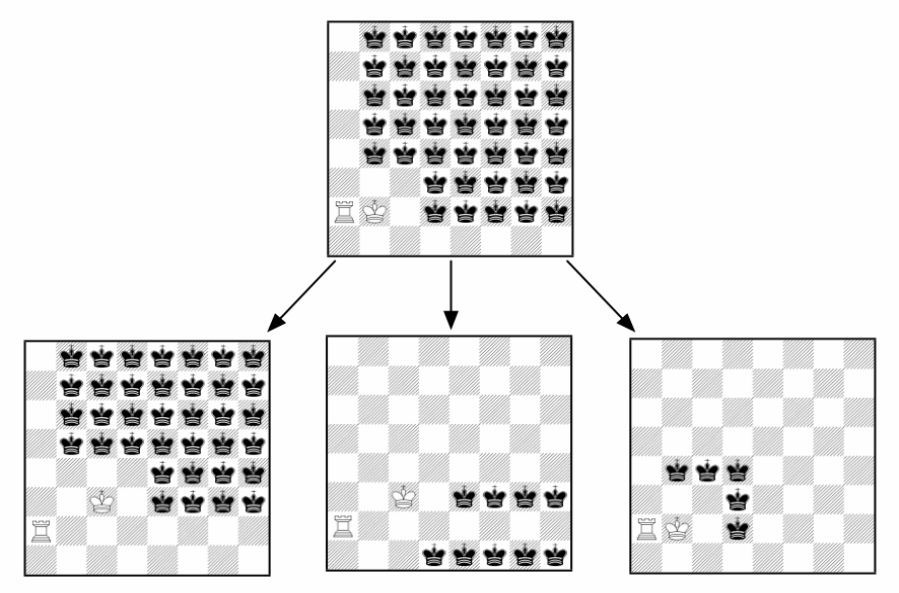
Size of KRK in Kriegspiel





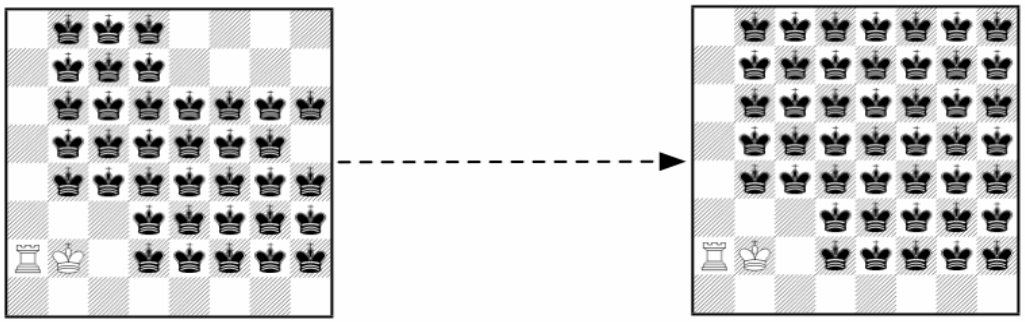
- 630 ways to place WK e WR;
- BK can in up to 52 positions
- $2^{52} * 630 \sim 10^{17}$ metapositions
- Many are irrelevant: indistinguishable after two plys

Retrograde solution



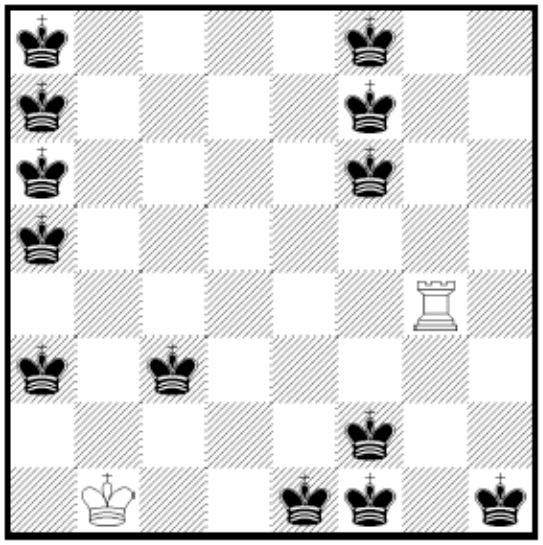
- Referee R can give a number of answers
- Eg.: Kc3 can get **silent**, **Check on file** or **illegal**
- A retrograde algorithm can explot these answers to reconstruct the startiing positions

The tablebase



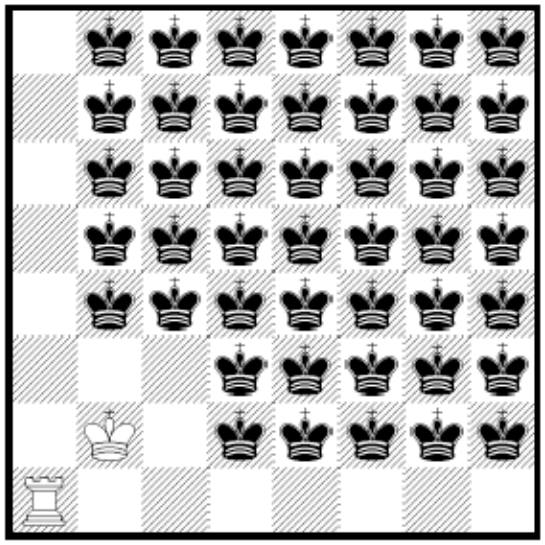
- If a given position is not in the tablebase we answer the largest metaposition with the related solution (=distance from checkmate)
- 10^6 positions, meaning that only one out 10^{11} is meaningful
- Longest sequence: 37 moves

Solving KRK



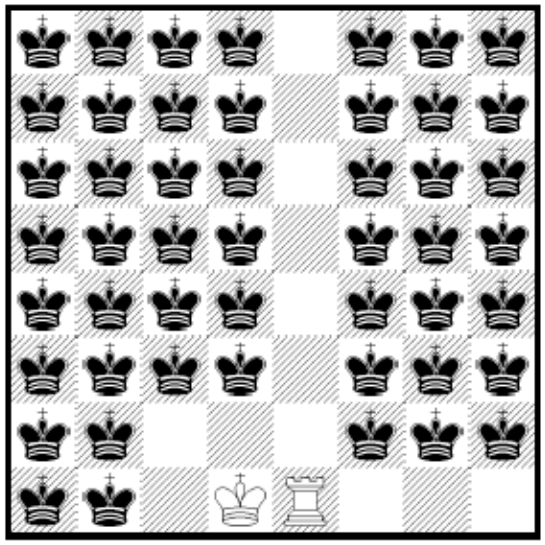
(a)

Mate in 37



(b)

(Boyce) Mate in 26

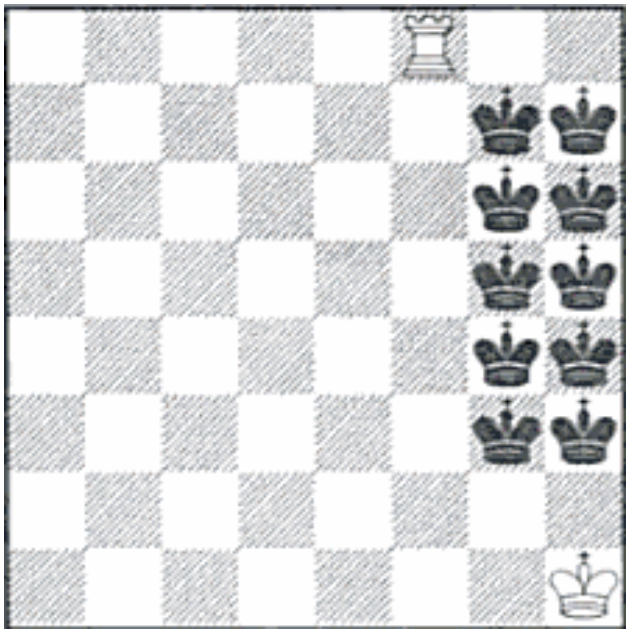


(c)

(Magari) Mate in 30

P.Ciancarini and GP.Favini, Solving Kriegspiel endings with brute force: the case of KR vs. K, 12th Int. Conf. On Advances in Computer Games, Pamplona, 2009

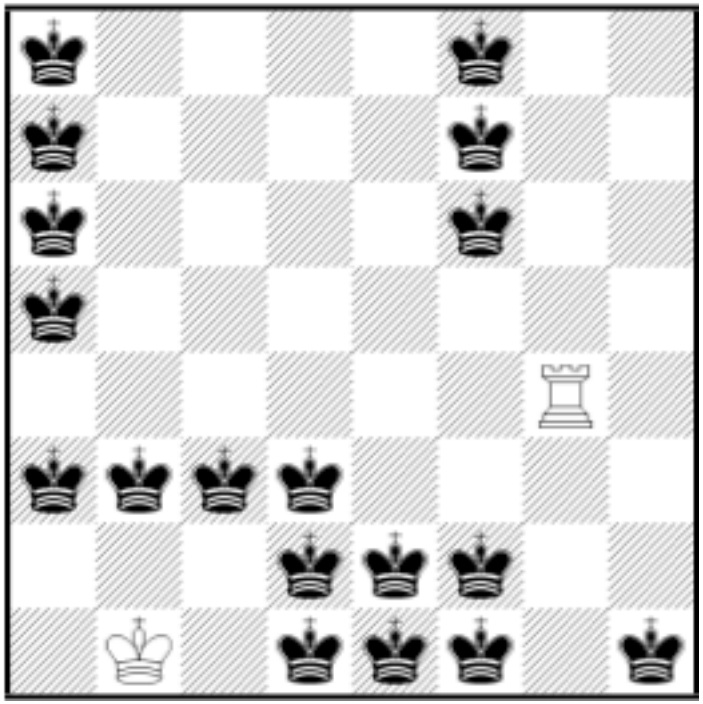
A Kriegspiel problem



Petkovic,
Chess and Mathematics,
Dover 1997

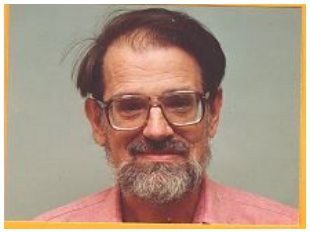
Checkmate in 14

The longest checkmate



- 37 moves
- Save the WR: Rf4, Kc2, Rf8, Kd3, Rg8, Rh8, Rh1, Rd1, Kc2
- Then “squeeze” the BK towards the border

Infinite board



Lloyd Shapley

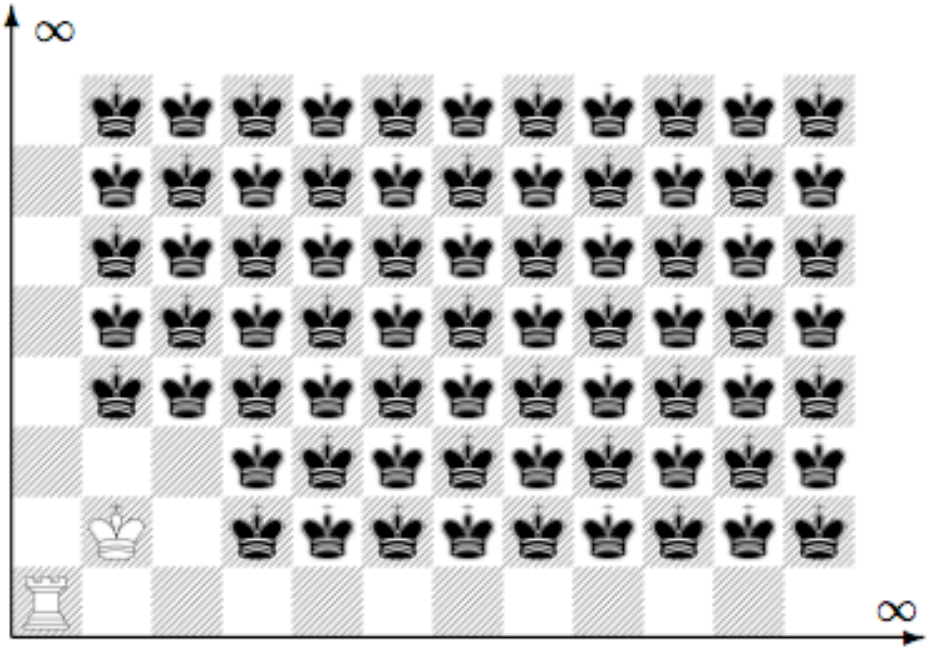


Figure 6.1: KRK on an infinite chessboard; the actual King is only one (this problem and its solution is due to Lloyd Shapley).

www.math.ucla.edu/~tom/papers/unpublished/kriegshap.pdf

Tablebase results

- We created tablebases for 4 endgames: KRK, KQK, KBBK and KBNK
- Tablebases range from 600,000 entries for KRK to 18 million entries for KBNK
- We finally solved KBNK, finding that it is always won in a fixed number of moves (89 at most). This problem was debated from the 1920s

Available: www.cs.unibo.it/~cianca/wwwpages/chesssite/kriegspiel/kriegspiel.html

MonteCarlo search for PIGs

- In a PIG, the game state is not fully known to the players, and minimax is computationally intractable
- In the last decade some progress has been obtained using MonteCarlo search techniques, that are very effective
- In some domains approaches based on MonteCarlo search are not enough to match the best humans

Progress

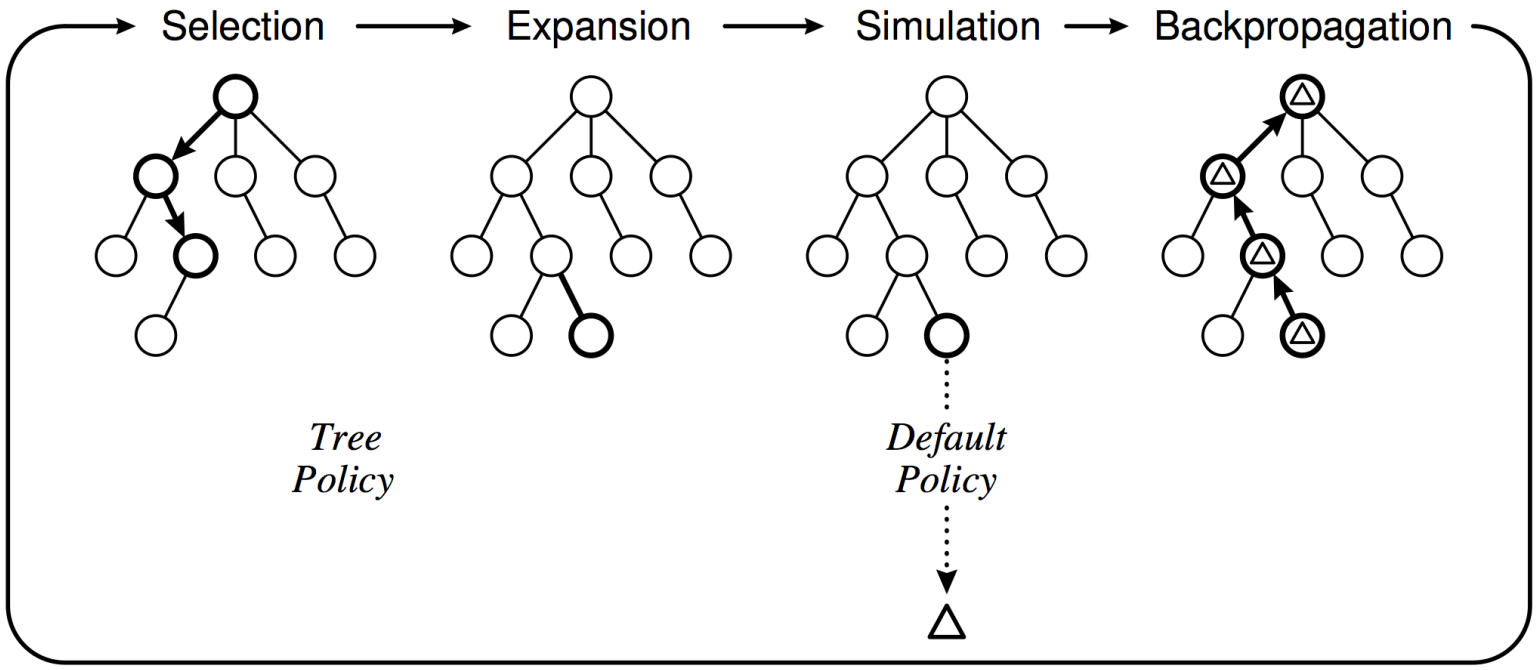
- In Chess or Go “progress” is crucial: programs rely upon minimax and evaluations which compare White and Black positions
- How can we measure the progress to victory if we do not see the opponent’s position?

MonteCarlo Tree Search

- Monte Carlo Tree Search (MCTS) has been used to play successfully complex board games such as Go
- It has also been used to play PIGs such as Phantom Go and Kriegspiel (Parker & Nau)
- MCTS builds a game tree in four steps that are repeated iteratively as long as time allows

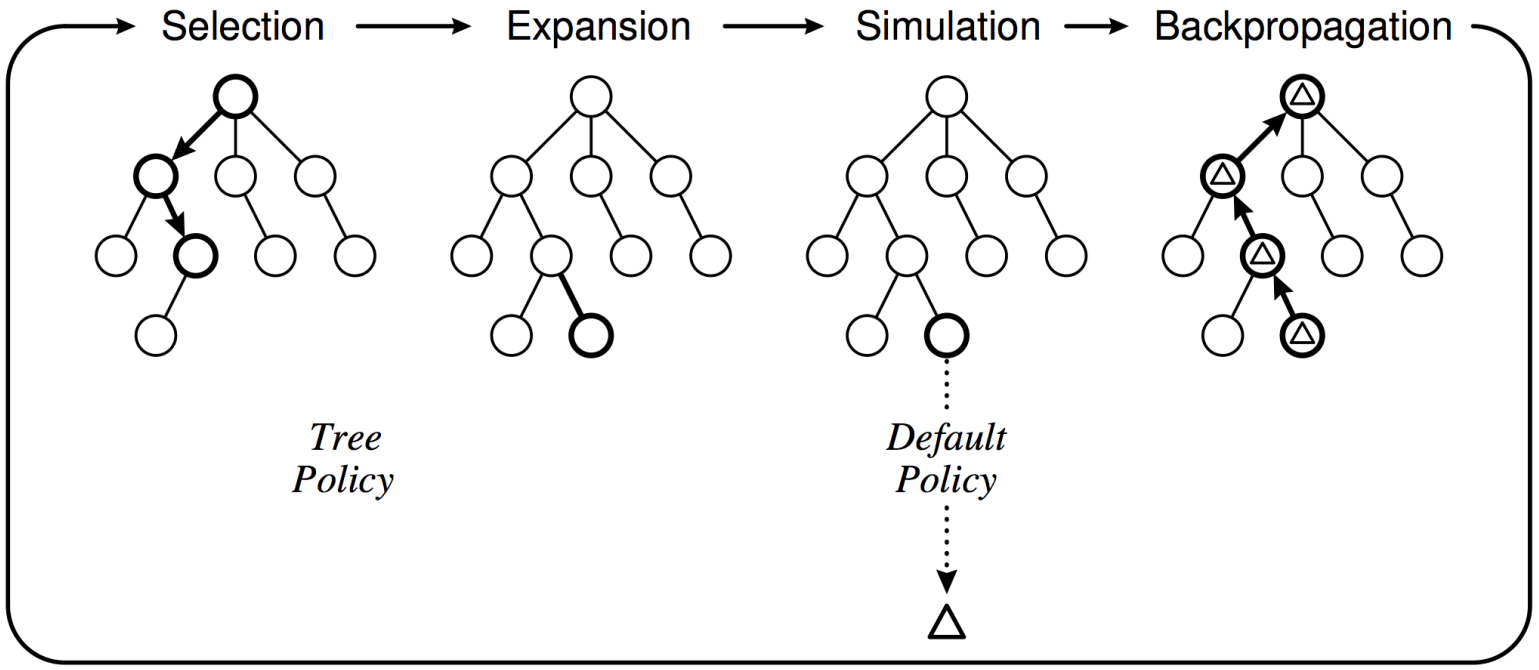
Monte Carlo Tree Search (1/4)

a) Selection: the algorithm selects a leaf node from the tree according to some policy (eg. UCT: Upper Confidence-bound applied to Trees); it has similarities to an exploration/ exploitation problem



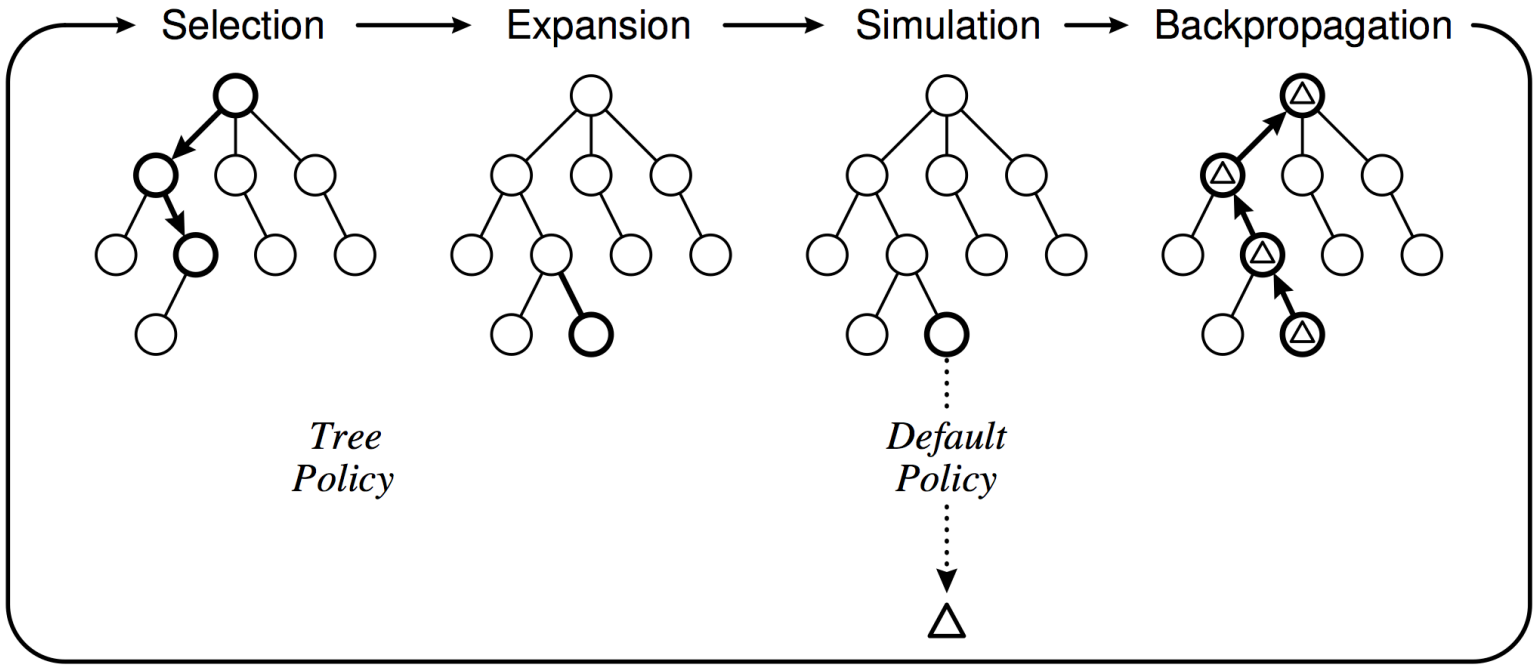
Monte Carlo Tree Search (2/4)

b) Expansion: optionally, the algorithm expands a leaf to the next depth level (for example, after *x* visits)



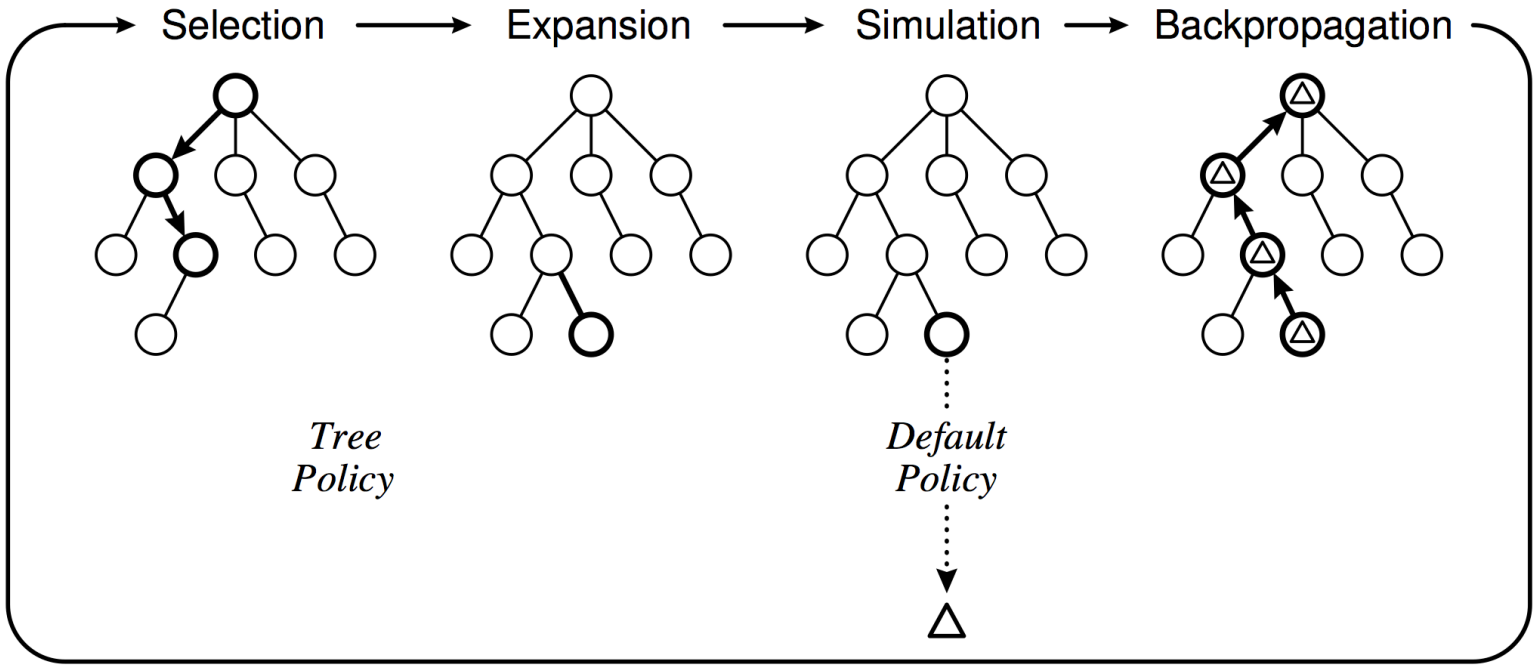
Monte Carlo Tree Search (3/4)

c) Simulation: A full game (or several) is simulated from a leaf node in the tree. Moves are random, but preferably guided by some heuristics



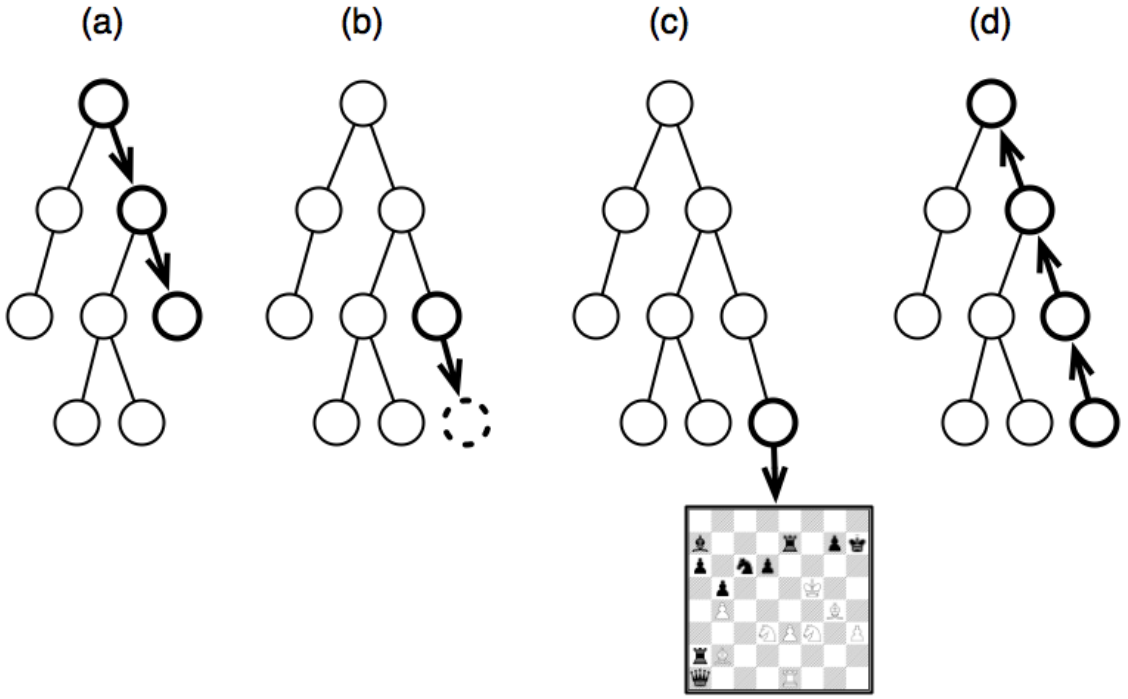
Monte Carlo Tree Search (4/4)

d) Backpropagation: The value of the simulated game(s) is propagated to the node's ancestors up to the root, usually by averaging it. This will affect subsequent selection steps



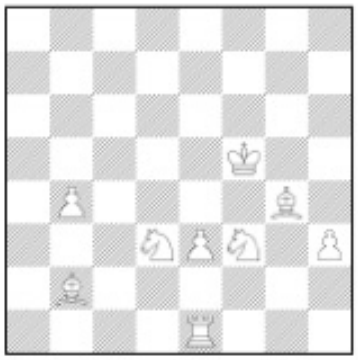
MonteCarlo search in Kriegspiel

- We adapted MCTS to play Kriegspiel better than our first program based on minimaxing a tree of metapositions



Three approaches

- How does MCTS perform in Kriegspiel?
- We have developed three different MCTS programs for Kriegspiel, that we call A, B and C
- Program A is textbook MCTS for Kriegspiel: for each simulation we create a random layout of the enemy pieces we believe are “onboard”



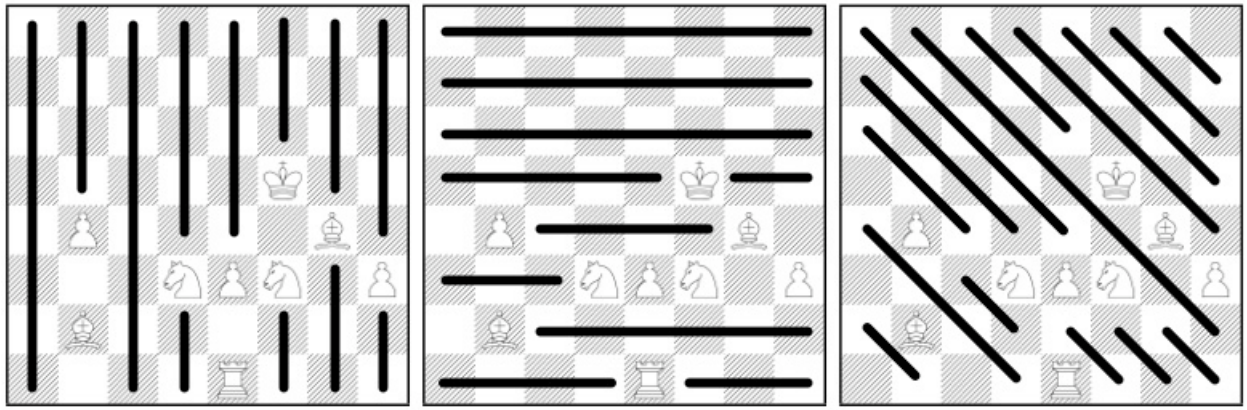

Problems with approach A

- It is difficult to create good random layouts for the opponent's pieces
- It is also time-consuming, which is very harmful to a Monte Carlo method
- Simulating the game with random moves makes for very long games that usually result in a draw regardless of the starting position
- Except in very specific scenarios, approach A turns out to be about as strong as the random player

Approach B (1/2)

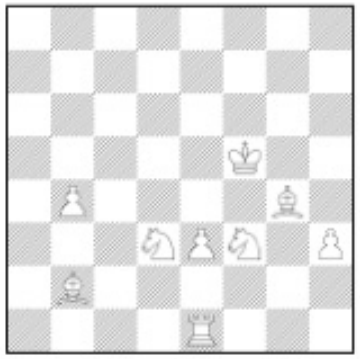
- Approach B tries neither to generate layouts for the enemy pieces, nor to move them on the board
- Only the player's moves and their consequences are simulated
- **The referee's messages are simulated:** the algorithm estimates the probability of each message being given by the referee (can be upgraded with opponent modeling data)
- Even if the probabilities are not very accurate, they are more reliable than generating random layouts - not to mention much faster

Spreading probabilities



- Every horizontal, vertical or diagonal sequence of 2 or more squares is considered
- For each sequence, the total probability of a piece (other than King and Pawn) being there is unchanged, but the probabilities for the individual squares are adjusted so they are closer to the average
- We ignore Knight moves for performance reasons

Approach B (2/2)



- After estimating that, for example, Bb2-a1 has a 20% chance of capturing something…

- … we run our Monte Carlo simulations as before, but we simulate our own moves and update the board according to the referee's simulated messages (as defined by a probability board)
- There is one more addition from approach A: a *simulation cutoff* after *k* moves

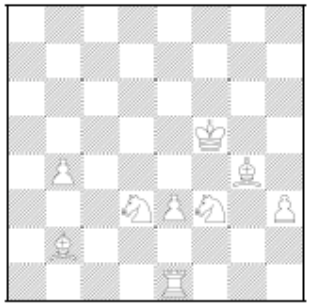
Simulation cutoff

- Achieving checkmate is approach A's major problem. Progress to checkmate happens very seldom with random moves, adding too much noise to the evaluation.
- To remedy this, we add a little game-specific knowledge to the algorithm
- Instead of running each simulation to the end, we stop it after *k* moves and adjudicate the game to the player that seems to be winning
- This function is much simpler than a true "evaluation function" and just counts the number of pieces each player has

Approach C

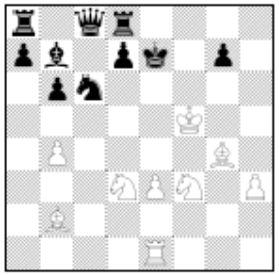
- The final approach is the same as approach B, with $k = 1$.
- Simulation is stopped after only one move.
- Since there is only one move to simulate, the result can be computed as a weighed average of the possible referee messages for that move.
- Every node is computed only once, saving time. Also, simulation is very accurate in the short range, though short-sighted (but the algorithm can use quiescence).

The three approaches

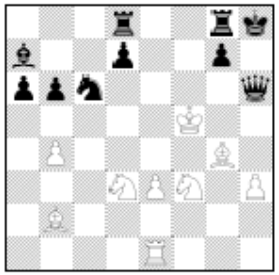


Value of b4-b5?

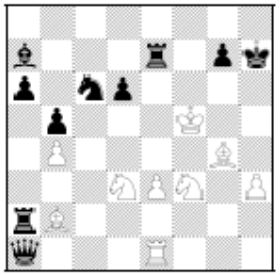
A



Umpire is silent



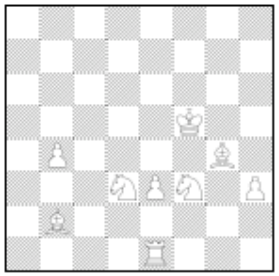
Pawn try



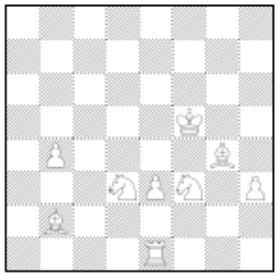
Illegal move

Full game simulations

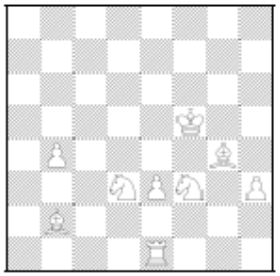
B



Silent (35%)



Pawn try (30%)



Illegal (35%)

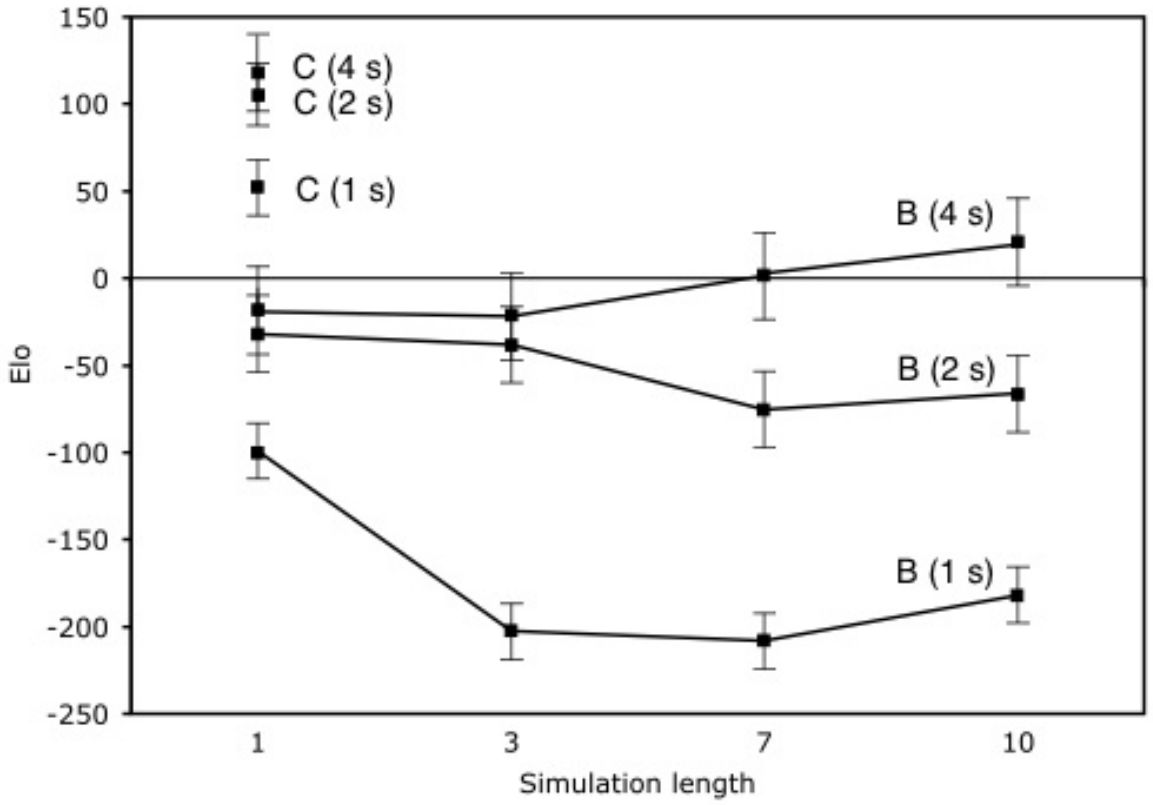
k-move simulations

C

value = 0.35*v(silent) + 0.3*v(pawn_try) + 0.35*v(illegal)

Weighed average of B (k=1)

Experimental results



k= 1÷10

- We test our B and C programs against an existing Kriegspiel player based on minimax search.
- We test a 1,2,4 seconds per move
- Surprisingly, short-sighted C performs best.

Results

- C performs better because it simulates better in the short range and can explore more nodes, but…
- … on higher time settings, B seems to be catching up. Eventually we expect B to be able to beat C
- Longer simulations perform better as soon as they can explore enough nodes.
- The minimax player is clearly defeated by the MonteCarlo approach

Results

- We call program C **Darkboard 2.0**.
- It plays better than Darkboard 1.0 (0.65-0.35 or about +120 Elo in direct matches)
- It won the 14th Computer Olympiad with a perfect score
- Consistently among top 20 players on the Internet Chess Club
- Still vulnerable to high-level human players

ICC Elo comparison

	Darkboard 1.0	Darkboard 2.0
Games played	2442	7121
Unique opponents	384 (6.36 games each)	589 (12.09 each)
Avg. Opponent Elo	1534	1646
Avg. Score	0.512	0.470
Avg. Elo	**1543**	**1626**
% of games vs higher Elo	47.0%	60.3%
Games vs Top 20 players	792 (32%)	2777 (39%)
Avg. Score vs Top 20 players	**0.171**	**0.26**

Some comments

- This scoring system is conservative by about 70-90 Elo due to ICC mechanics.
- Darkboard 1.0 played its games in 2006 and 2007, 2.0 played in 2008 and 2009.
- DB 1.0 faced and defeated many weak opponents, DB 2.0 played against the stronger players more often.
- The Top 20 players considered were the same for both programs, so the confrontation is direct.

Applicability

- Our Monte Carlo approaches are applicable to any scenario with high uncertainty and referee-mediated knowledge (e.g. sensors).

- Imperfect information tablebases are likewise applicable to any situation in which one player can force a win.

The future

- Some more improvements are necessary before we can really challenge the best humans:
  - Planning
  - More learning (currently only rote learning)
  - Recursive opponent models (“he knows that I know that he knows…”)
  - Better simulation policies

Planning

- Some PIG can be modeled with a game tree whose branching factor is very huge and even grows along the game
- **Planning**: ”*a selective approach only searching "important" branches as the most promising ones*” (C.Shannon)
- Problem: how to use planning in a search based on MonteCarlo search

Planning

Human players do not build a complete game tree when they choose a move: a common approach in many games is to identify states that verify a set of ”known relationships” as a favorable state.

Such ”relationships” may be identified as ”strategical elements”, and we can use them as goals for a long term plan

Conclusions

- PIGs are especially interesting for Game Theorists, because their mathematical modeling is still incomplete (eg. wrt planning)
- Kriegspiel is interesting as model of warfare and in general for taking decisions in condition of uncertainty

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- Harsanyi, Games with Incomplete Information, *The American Economic Review, 85:3(291-303),* 1995
- Perla, *The Art of Wargaming: a guide for professionals and hobbysts*, 1990
- Smith and Nau, Strategic Planning for Imperfect-Information Games*, AAAI Symposium on Games: Planning and Learning,* 1993

Research works on Kiegspiel

- Definition of game-theoretic algorithms for simple endings (Shapley, Boyce, Ferguson, Ciancarini and others)
- Planning based on MonteCarlo sampling (Parker Nau & Subrahmanian, IJCAI 2005)
- AND-OR search of belief-state trees (Russell & Wolfe, IJCAI 2005)
- Reasoning about partially observed actions (Rance Vogel & Amir AAAI 2006)
- Towards strategic Kriegspiel play with opponent modeling (Del Giudice Gmytrasiewicz & Bryan 2009)
- Parallelizing Information Set Generation for Game Tree Search Applications (Richards et al. 2012)

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- A.Bolognesi, P.Ciancarini: Computer Programming of Kriegspiel Endings: The Case of KR versus K. *Advances in Computer Games* 325-342, 2003
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- P.Ciancarini, A.Gasparro, Priority planning in Kriegspiel, Proc. ICEC, 333-340, 2012

Question time

- Thank you for your attention!