Game Playing AI

Guest Lecture in Structured Programming

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Many thanks to Stephen Gould!
Slides partially build upon his lecture from 2019.

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College of Engineering and Computer Science
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Australian National University

Outline for Today

- Motivation: Why Solving Games Automatically Anyways?
- What are Games? (A few Definitions)
- Solving Small Games
  - MiniMax
  - α/β Pruning
- Games with Chance
- Solving Large Games
- Defeating Dragons with AI
- Game AI Success Story

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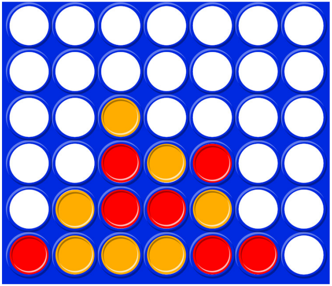

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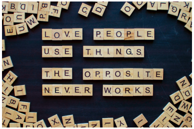
  - Robotics or Multi-Agent-Planning (though this is often cooperative, whereas we take a look at antagonistic games)
  - Economics! Cf. **game theory** (look up: *Nash Equilibrium* and *Prisoner's Dilemma*)

What are Games? Which Kinds Exist?

A **game** consists of a set of one or more **players**, a set of **moves** for the players, and a specification of **payoffs** (outcomes) for each combination of **strategies** (also called policy).

What kinds of restrictions can games have?



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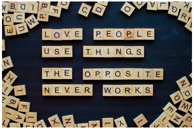

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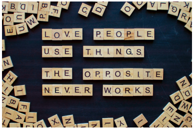

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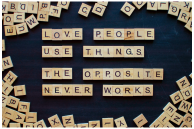

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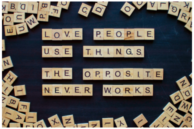
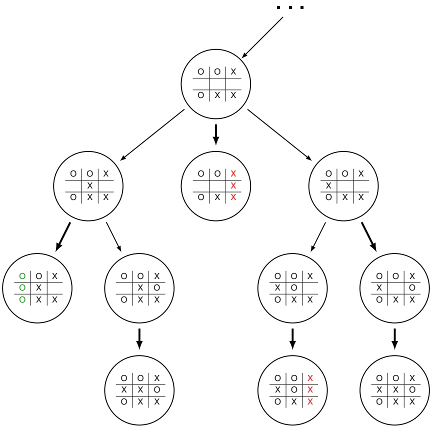
- Games with chance (randomness) vs. games without chance



What's a Strategy?

A **strategy** defines a complete plan of action for a given player.

Given enough processing time an **optimal strategy** can be found for games of **perfect information** by enumerating paths of a **game tree**. However, in practice this can only be done for small games.



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- Game AI (strategy) vs. game theoretic outcome!

What's the game theoretic outcome?

- The outcome of the game assuming all players play *rational*.
- Rationality = optimization of expected reward.
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- Just because we have an AI that beats all humans, it doesn't mean the game is solved!

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MiniMax — How to Solve Small Games?

Using search to solve a game:

- If the game tree is "sufficiently small" we can search in it to find and extract a strategy.
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Consider two players, MAX and MIN. MAX tries to maximize his/her own score, and player MIN tries to minimize it.

We assume that the players are rational.

MiniMax — The MiniMax Algorithm

The MiniMax algorithm allows each player to compute their optimal move on a game tree of alternating MAX and MIN nodes.

The value of a node is the payoff for a game that is played optimally from that node until the end of the game.

max-value(s)
- **if** *state s is a leaf* **then**
  - **return** payoff(s)
- $v := -\infty$
- **forall** *successor states s' of s* **do**
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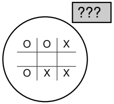
MiniMax — Example: Tic Tac Toe

MAX player plays X, MIN plays O. Outcomes (black boxes) are from the perspective of the MAX player (i.e., 1 is a win, -1 a loss, 0 a draw).

MAX



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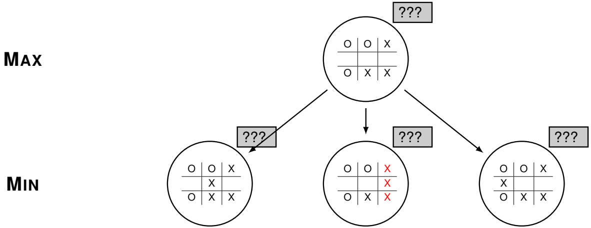

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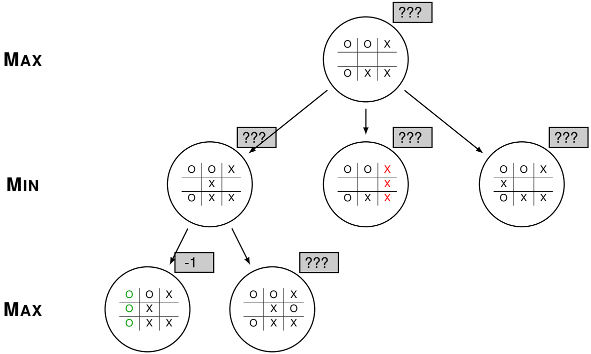

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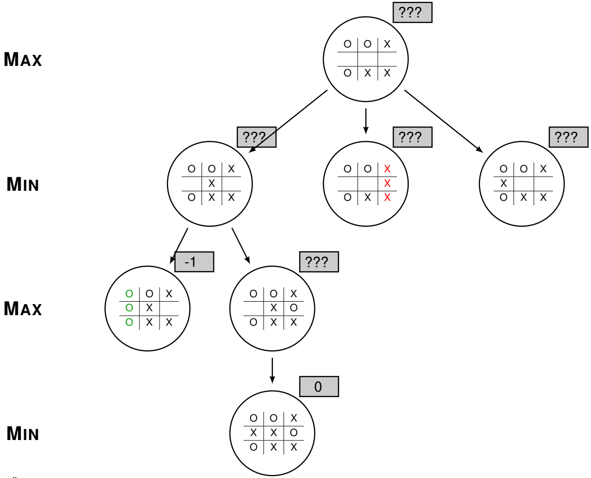

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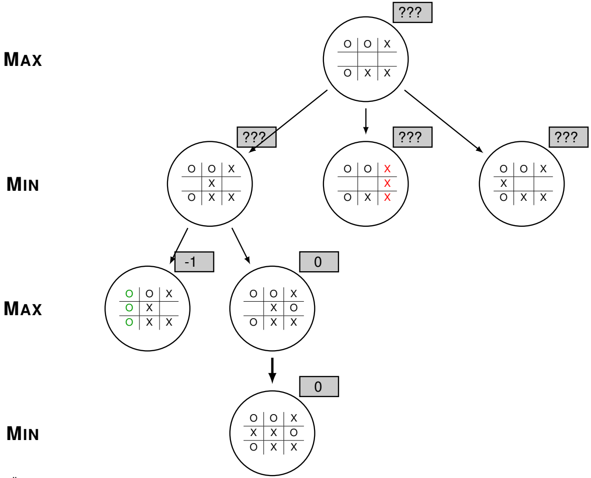

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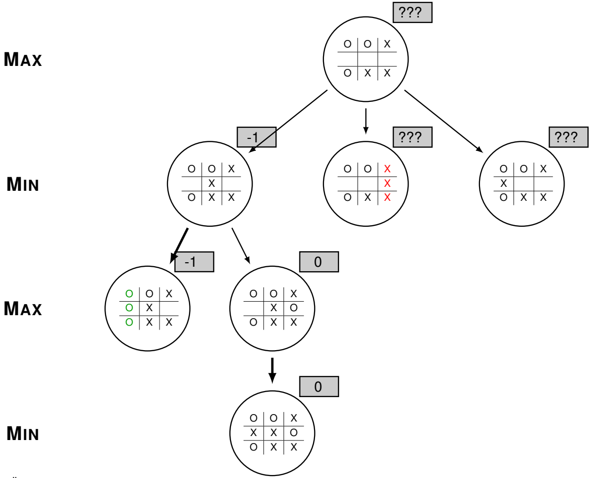

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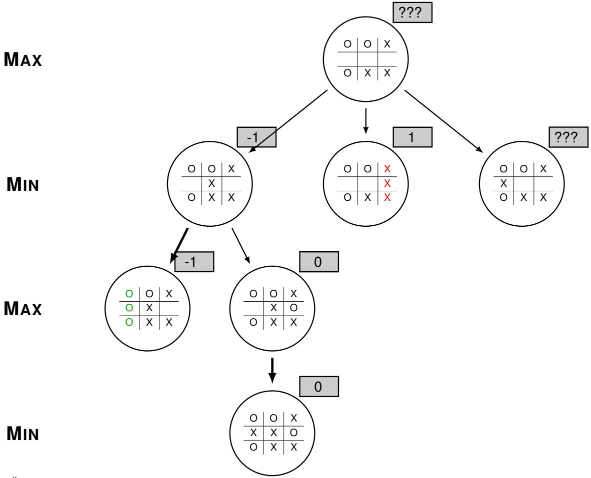

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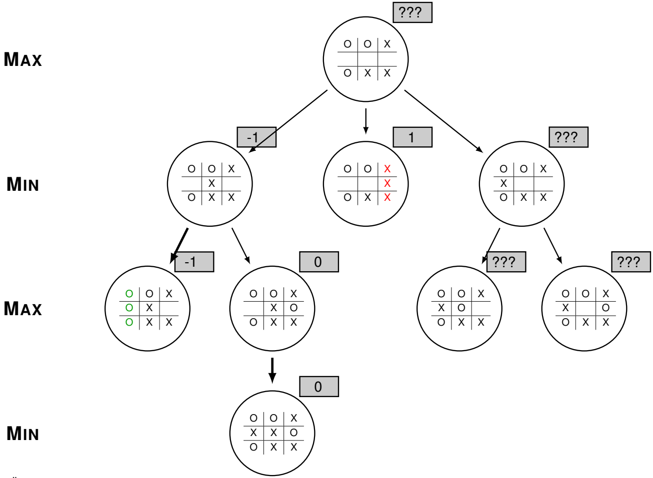

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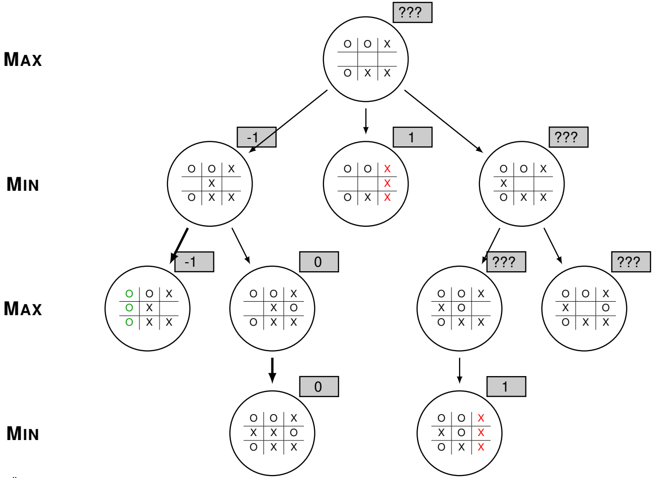

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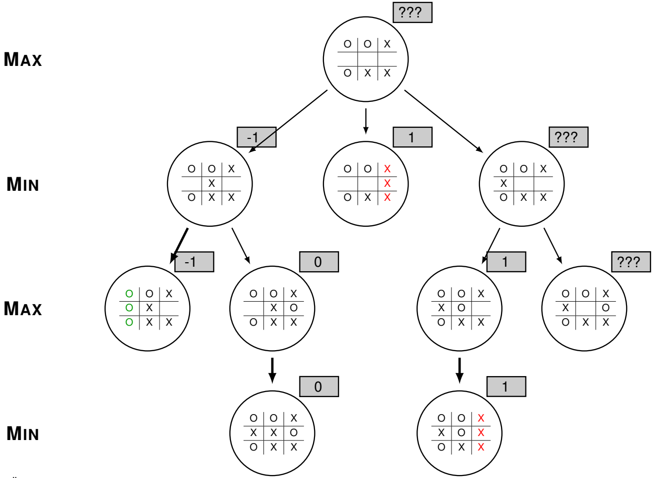

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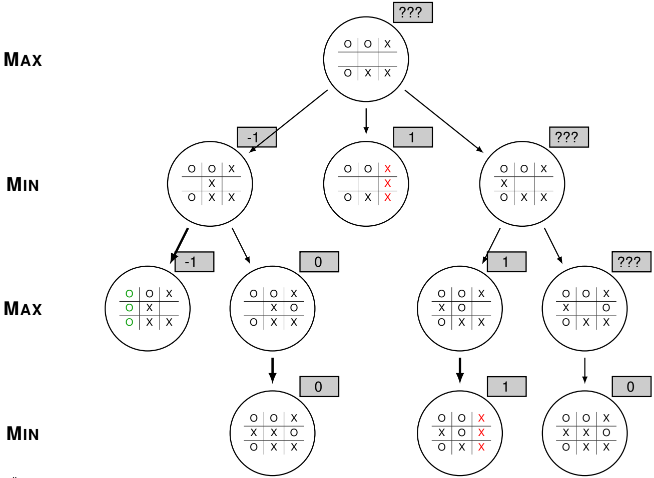

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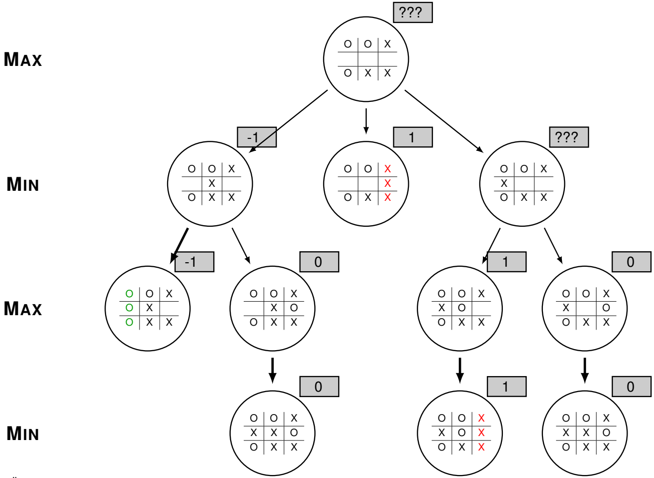

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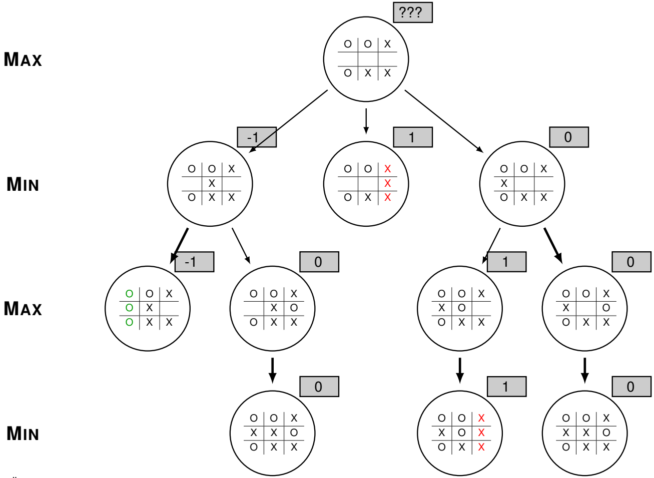

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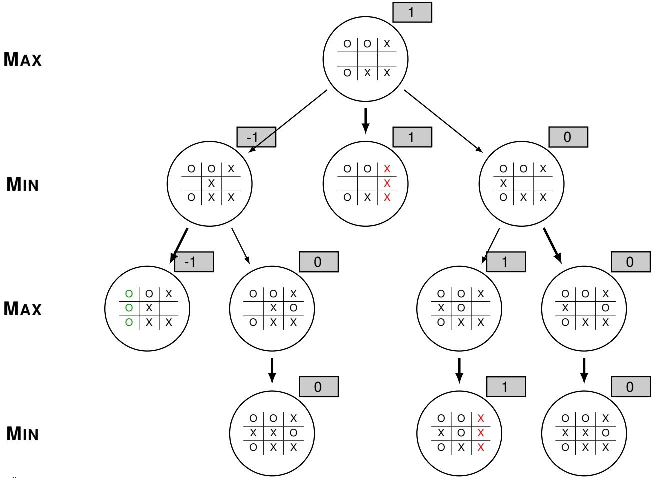

MiniMax — Space and Time Complexities

What is the runtime of MiniMax?

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What is the space requirement of MiniMax?

- We perform a depth-first search!
- So only the longest path needs to be stored.

$\rightarrow$ Space is in $O(b \cdot d)$ (linear)

α/β Pruning — Can we do better?

- MiniMax suffers from the problem that the number of game states it has to examine is *always* exponential in the number of moves.
- α/β pruning is a method for reducing the number of nodes that need to be evaluated by only considering nodes that may be reached in game play.
- Alpha-beta pruning places bounds on the values appearing anywhere along a path:
  - α is the best (highest) value found so far for MAX
  - β is the best (lowest) value found so far for MIN

  α and β propagate down the game tree.

  v propagates up the game tree.

α/β Pruning — The MiniMax Algorithm Extended By α/β Pruning

Keep in mind:

- α is the best value found so far for MAX, initialize with $-\infty$.
- β is the best value found so far for MIN, initialize with ∞.

max-value(s, α, β)
- **if** *state s is a leaf* **then**
  - **return** payoff(s)
- $v := -\infty$
- **forall** *successor states* s' *of s* **do**
  - $v := \max\{v, \text{min-value}(s', \alpha, \beta)\}$
  - **if** $v \geq \beta$ **then**
    - **return** v
  - $\alpha := \max\{\alpha, v\}$
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- **forall** *successor states* s' *of s* **do**
  - $v := \min\{v, \text{max-value}(s', \alpha, \beta)\}$
  - **if** $v \leq \alpha$ **then**
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  - $\beta := \min\{\beta, v\}$
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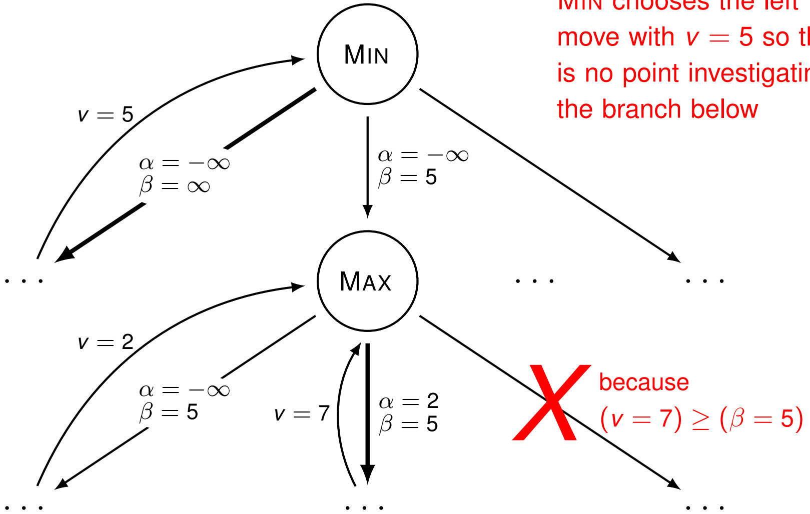
α/β Pruning — Idea Behind Pruning: When and Why?

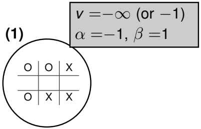


MIN chooses the left move with $v = 5$ so there is no point investigating the branch below

α/β Pruning — Example: Tic Tac Toe

Start with $\alpha = -1$ (rather than $-\infty$) and $\beta = 1$ (rather than ∞)

MAX



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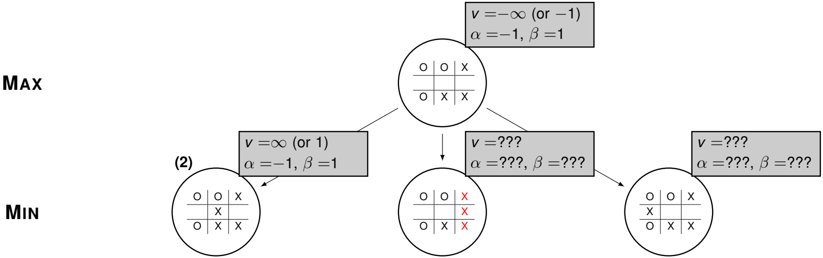

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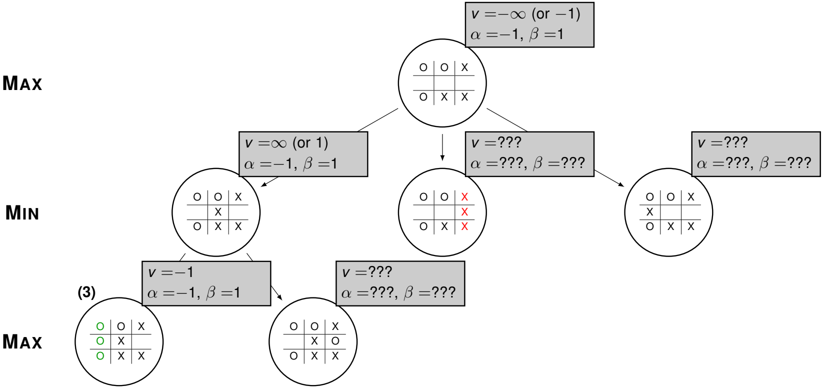

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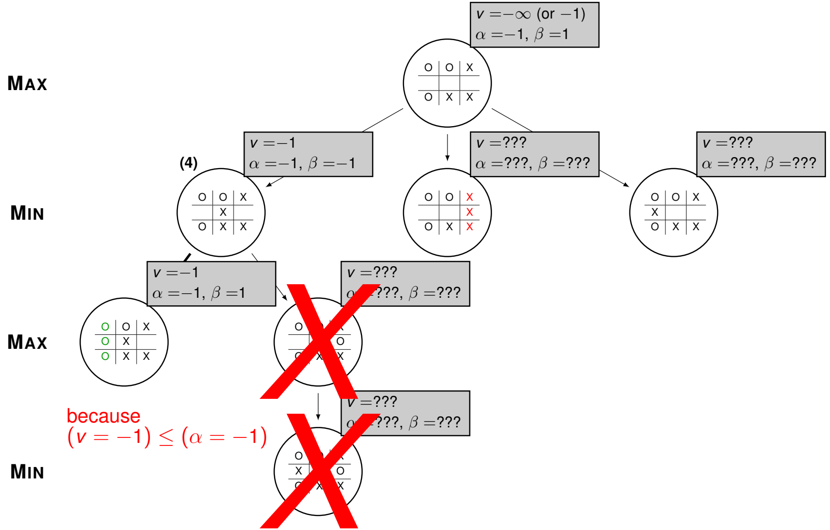

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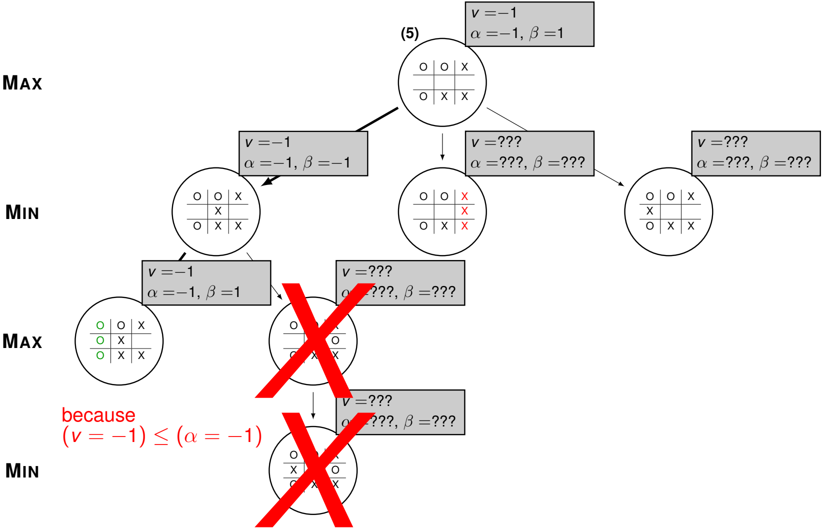

because
$(v = -1) \leq (\alpha = -1)$

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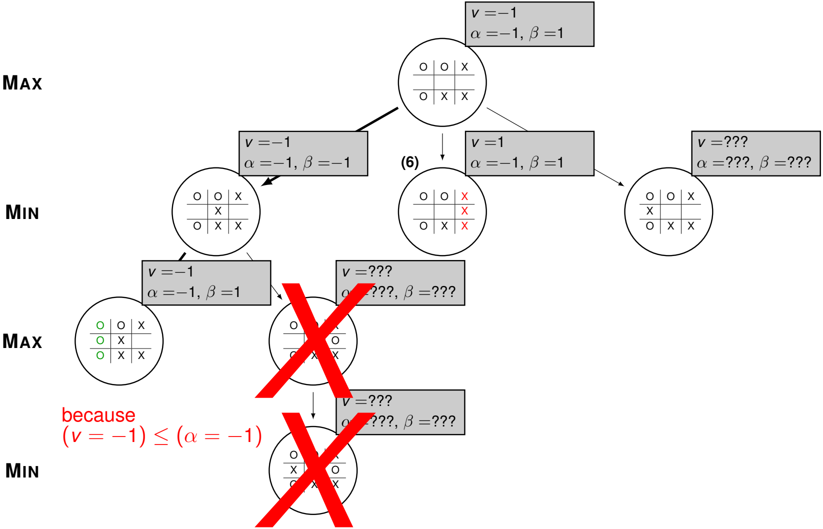

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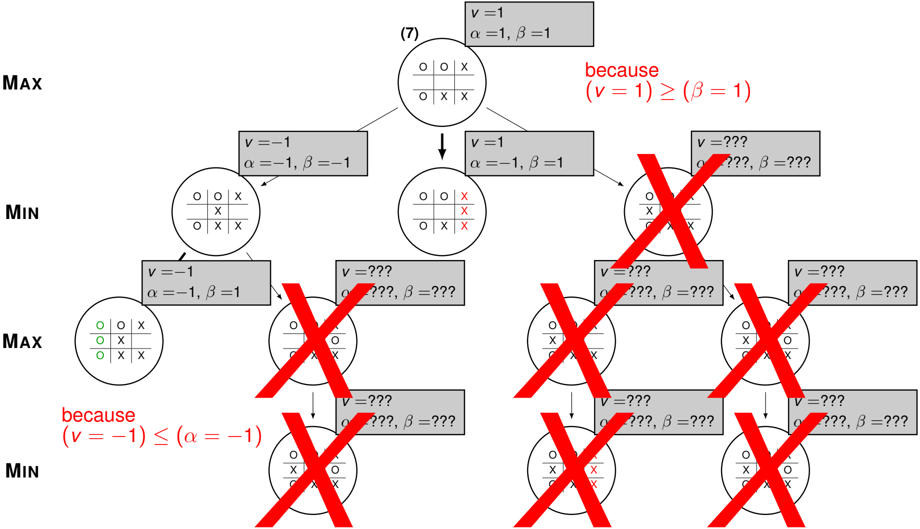


α/β Pruning — Space and Time Complexities

What is the runtime (and space requirements) of α/β pruning?

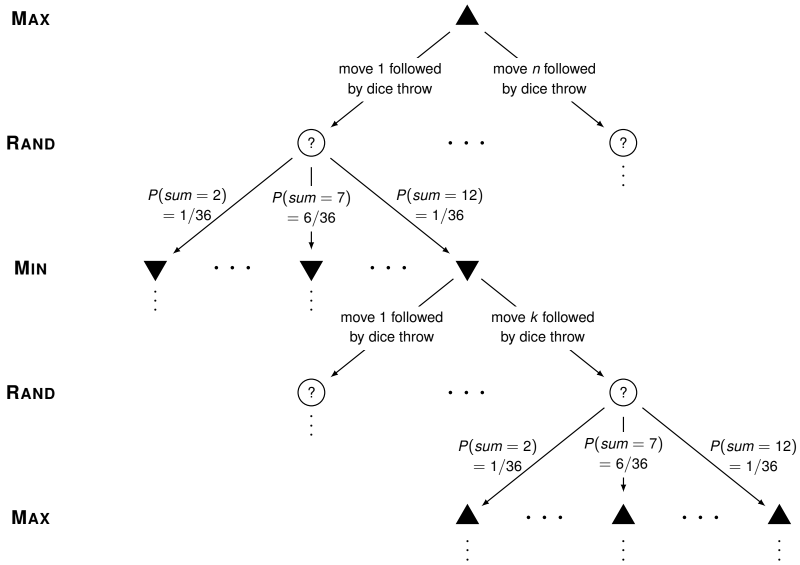
- In the worst case: identical to MiniMax! If nothing can be pruned.
- On average: Complexities omitted. (Due to lack of time.)
- This can happen depending on the order in which edges are traversed/payoffs are discovered.
- In practice, it is very unlikely that no pruning occurs, so *always* choose α/β pruning over MiniMax!

How to Deal with Randomness?

- A random decision can be regarded as the move of yet another player!
- Certainly that's not another MAX player! I.e, the "environment" (the random decision) will not always play in our favor!
- But what is it, then?
  - Another MIN player? (Too pessimistic...)
  - If we want to play *rational*, we maximize the expectation!

    $$value(s) = \sum_{\text{successor states } s' \text{ of } s} P(s') \cdot value(s')$$

Illustration For a 2-Player Game With Throwing Two Dice, Counting Their Sum



The "Size" of Games

When is using MiniMax and α/β Pruning still feasible?

- Recall that the complexity of MiniMax (and α/β!) is exponential! I.e., in $O(b^d)$, with
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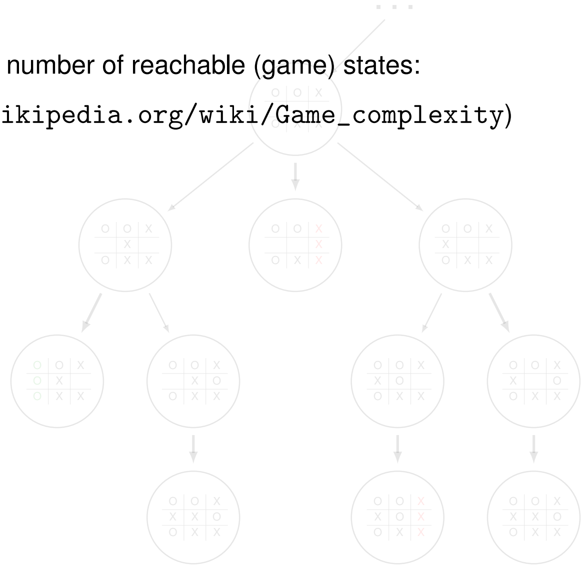
  - b, the branching factor (available moves per state)
  - d, the depth (number of moves until game ends)
- For some games that is simply too large!
- So, let's take a look at some examples...

The “Size” of Games: Tic Tac Toe

Examples for (estimated) number of reachable (game) states:

(Source: `https://en.wikipedia.org/wiki/Game_complexity`)



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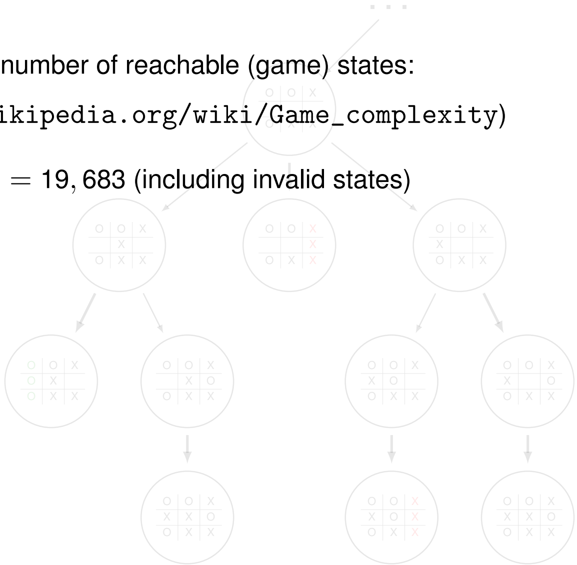

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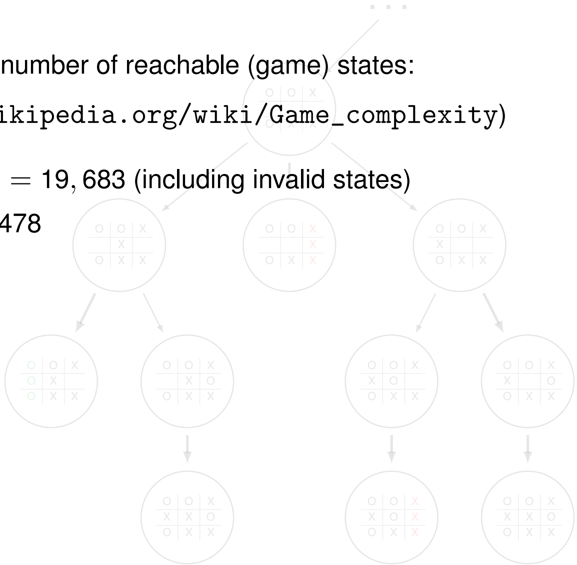

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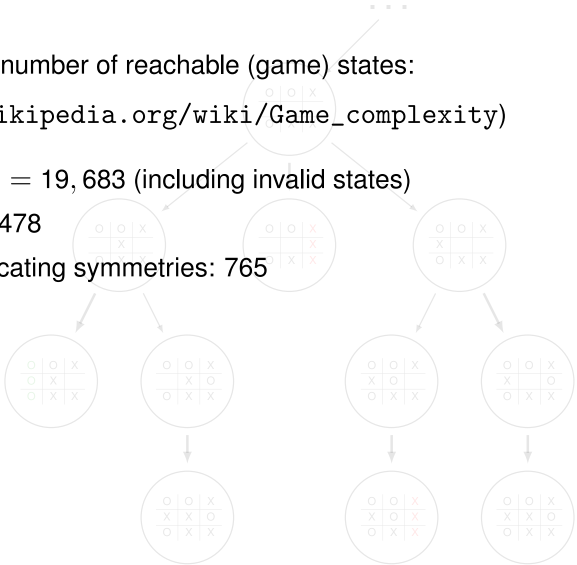
- Actual maximum: $5,478$
- Maximum after duplicating symmetries: 765



The "Size" of Games: Tic Tac Toe

Examples for (estimated) number of reachable (game) states:

(Source: `https://en.wikipedia.org/wiki/Game_complexity`)

- Rough maximum: $3^9 = 19,683$ (including invalid states)
- Actual maximum: $5,478$
- Maximum after duplicating symmetries: 765
- There are still $26,830$ possible *games*!
  (For those states with eliminated duplicates.)
  What's a "game"?
  A path in the MiniMax tree!

The “Size” of Games: Connect 4

Examples for (estimated) number of reachable (game) states:

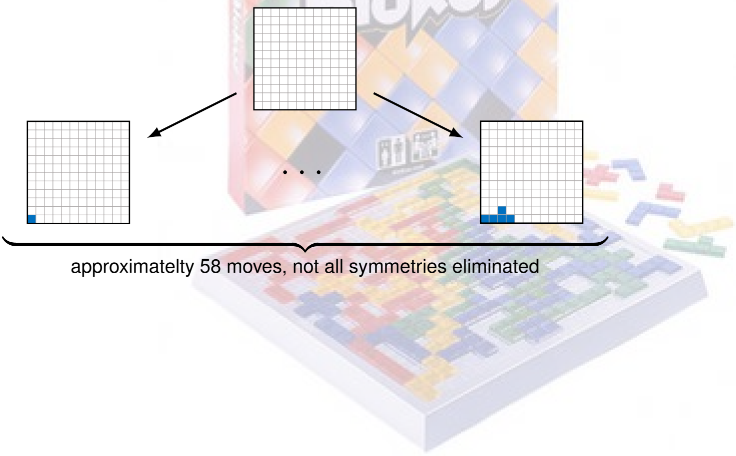
(Source: `https://en.wikipedia.org/wiki/Connect_Four`)

- Rough maximum: $3^{7\cdot 6} < 1.110^{20}$ (including invalid states)
- Actual maximum: $4,531,985,219,092 \approx 4.5 \cdot 10^{12}$ (still including symmetries)
- First solved, independently, by James Dow Allen (October 1, 1988), and Victor Allis (October 16, 1988).
- Note that today it can also be solved using α/β pruning!

The “Size” of Games: Blokus

Examples for (estimated) number of reachable (game) states:

(Source: by Stephen Gould, previous year(s))



The “Size” of Games: Blokus

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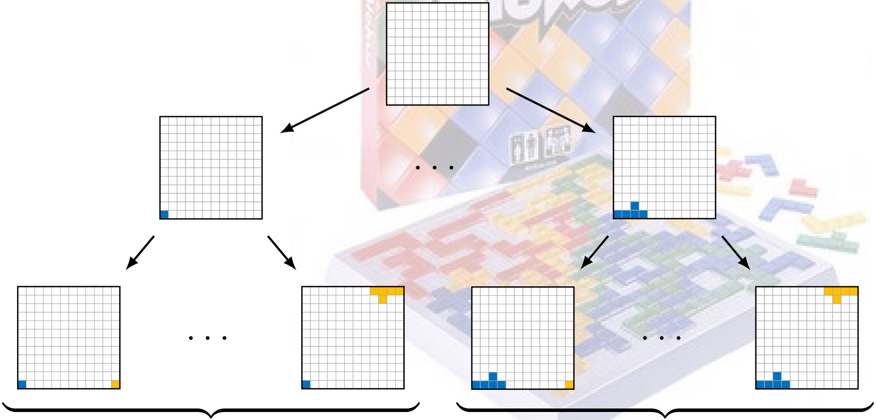

approx. $2 \cdot 58$ moves, symmetries as before

approx. 116 moves, symmetries as before

The “Size” of Games: Blokus

Examples for (estimated) number of reachable (game) states:

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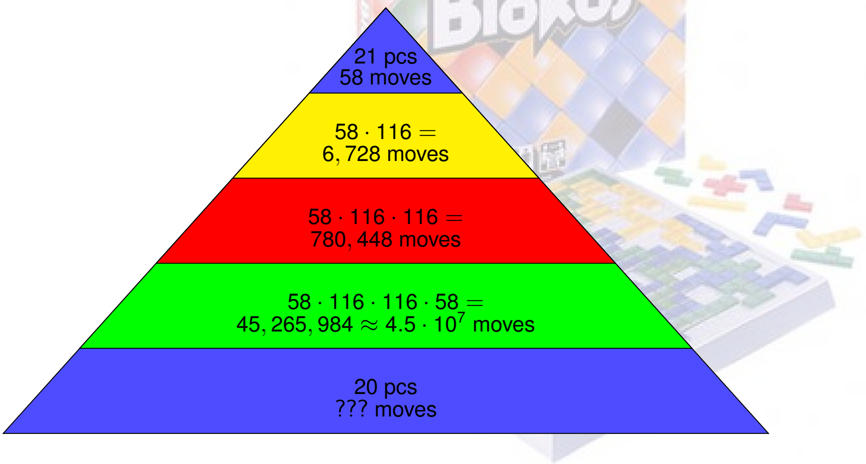
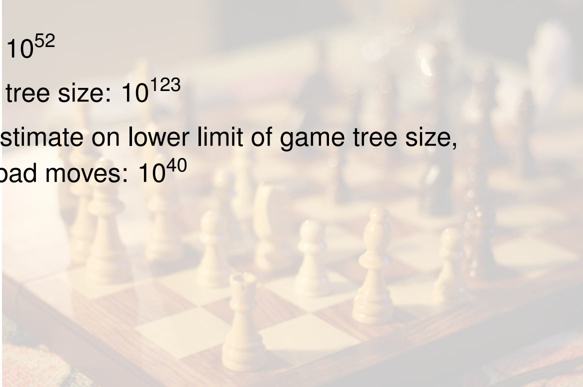


The “Size” of Games: Chess

Examples for (estimated) number of reachable (game) states:

(Source: `https://en.wikipedia.org/wiki/Shannon_number`)

- Some maximum: $5 \cdot 10^{52}$
- Lower limit on game tree size: 10^{123}
- More conservative estimate on lower limit of game tree size, eliminating obvious bad moves: 10^{40}

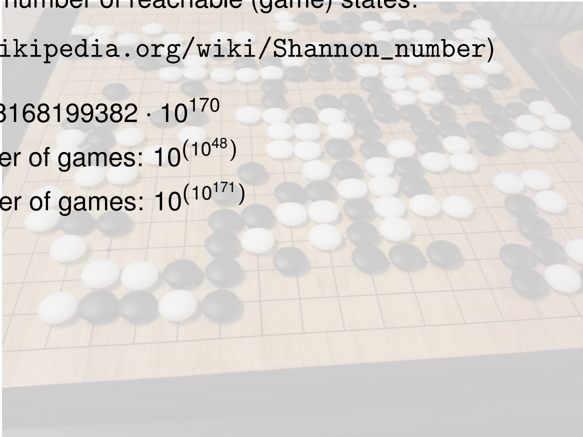


The "Size" of Games: Go

Examples for (estimated) number of reachable (game) states:

(Source: `https://en.wikipedia.org/wiki/Shannon_number`)

- Legal positions: $2.08168199382 \cdot 10^{170}$
- Lower limit on number of games: $10^{(10^{48})}$
- Upper limit on number of games: $10^{(10^{171})}$



How to deal with large games?

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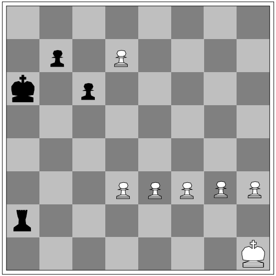

Black to move

Title: *Artificial Intelligence: A Modern Approach (3rd Ed.)*
Authors: *Stuart Russel* and *Peter Norvig*
URL: `https://aima.cs.berkeley.edu/`

Estimate per piece:

- pawn: 1 pt
- knight/bishop: 3 pts
- rook: 5 pts
- queen: 9 pts

Estimate: Black: 7 pts versus White: 6 pts
$\rightarrow$ Black leading! (Only *very* slightly.)

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    Machine learning techniques are often used to find a good static evaluation function based on a linear combination of features:

    $$\hat{v}(s) = w_1 f_1(s) + \cdots + w_n f_n(s)$$

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    Note the similarity to chess!

    - $w_1 = 1$, $f_1(s) =$ number of pawns in s
    - $w_2 = 3$, $f_2(s) =$ number of knights/bishops in s
    - ...

How to deal with large games?

So, what to do for (too) large games?

- Don't compute the entire game tree!
- Stop at certain nodes and *estimate* their payoff! But how?
  - hand-crafted heuristics
  - learned heuristics
  - simulate a game, use the outcome as estimate

  Monte-Carlo Tree Search is a well-known algorithm exploiting this idea. It works in four phases:

  - *Selection* (select a non-terminal leaf based on current strategy)
  - *Expansion* (expand the selected node)
  - *Simulation* (play a random game to the end)
  - *Backpropagation* (use the outcome to update strategy)

  Interested? See, e.g.,
  `https://www.youtube.com/watch?v=UXW2yZndl7U`
  (15:30, lecture by Dr. John Levine from Univ. of Strathclyde)

When to use heuristics?

- In standard MiniMax or *alpha/beta* pruning, we make a **terminal test** to obtain the payoff, or continue expanding. With heuristics, we instead make a **cut-off test** to check whether we should stop expansion and *estimate* the payoff of the current node.

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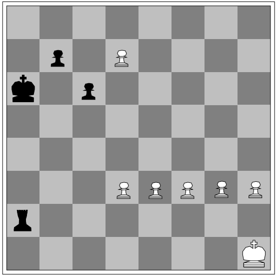
- What about using a fixed depth as cut-off test? $\rightarrow$ Suffers from the **horizon problem**:



Black to move

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White can promote a pawn into a queen on his next move! So the cut-off test should be negative in this state.

The Assignment: Tsuro of the Seas

But let's start with Tsuro, the "underlying game mechanics".

Figure: YouTube video: https://www.youtube.com/watch?v=MGvY3jsLN1I (1:25) Code: M-G-v-Y-3-j-s-L-N-1(one)-I(capital-i)

The Assignment: Tsuro of the Seas

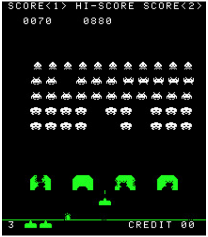
Tsuro of the Seas: Ultra-short introduction

Figure: YouTube video: https://www.youtube.com/watch?v=ziQS8rcT5EA (we just take a glance from 5:04 to 5:58) Code: z-i-Q-S-8-r-c-T-5-E-A

Regarding the game rules: Please stick to the ones officially provided by Steve Blackburn!

Mile Stones in AI Game Playing

1959 Arthur Samuel develops Checkers playing program



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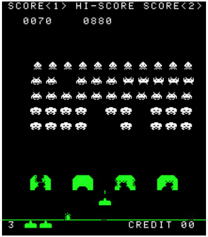

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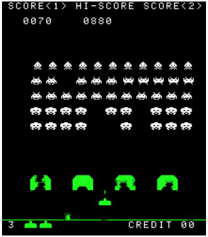

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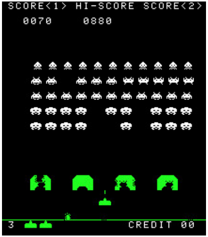

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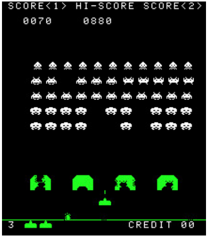

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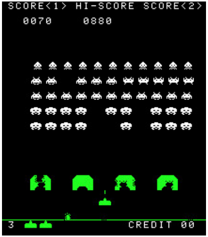

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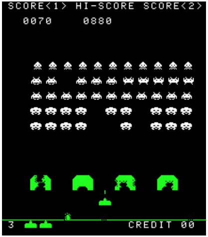
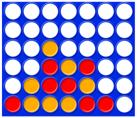
- 2017 AlphaZero learns Go, Chess, and Shogi from scratch (and beats AlphaGo)





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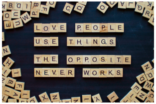

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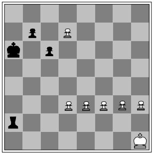

Black to move

By Stuart Russel and Peter Norvig
from their book *Artificial Intelligence: A Modern Approach (3rd Ed.)*
Availble freely for teaching on `https://aima.cs.berkeley.edu/`

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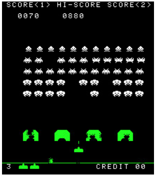

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