

COMENIUS UNIVERSITY IN BRATISLAVA
FACULTY OF MATHEMATICS, PHYSICS AND INFORMATICS



ARTIFICIAL NEURAL NETWORK AS AN OPPONENT IN QUORIDOR

Bachelor Thesis

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Bachelor Thesis

Study programme: Applied Informatics
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Advisor: Mgr. Peter Gergel'

Declaration of Authorship

I do solemnly declare that I have written the presented thesis by myself under careful supervision of my thesis advisor without undue help from a second person other than that specified.

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Acknowledgement

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Abstract

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0.1 Introduction

0.1.1 Quoridor Rules

Quoridor is abstract board strategy game for 2 or 4 players with size of 9x9 (81) squares. This thesis covers 2 player version of this game.

Each player starts with a single pawn in the center of the edge on the opposite side as the opponent. The goal for each player is to reach the opposite edge.

Player also starts with 10 walls (fences) in the stock. Walls are two space wide and can be placed in the groove that runs between the spaces. Placed wall blocks pawns paths forcing them to go around it. Walls once placed can not be moved nor removed. Wall can not be placed to the position already occupied or crossing by other wall. Also, wall can not cut off the only remaining path of any pawn to his goal.

When player is on turn, he must place wall, if he has left some, or move his pawn to adjacent (not diagonal and unoccupied) space. If opponent's pawn stands on an adjacent space, current player can jump with his pawn to all the places where the opponent pawn can move.

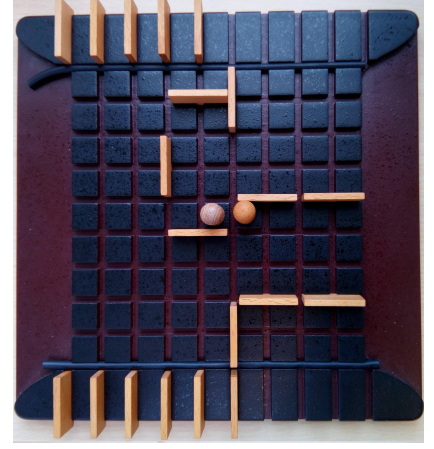


fig. 1: real board

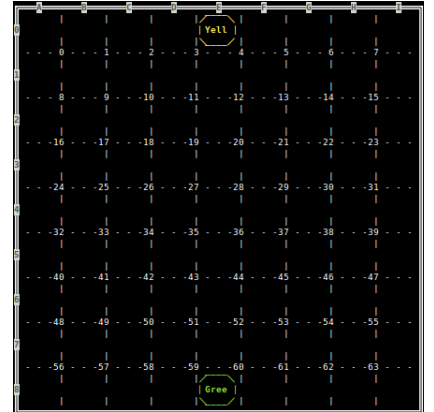


fig. 2: game start

0.1.2 Q-Learning

Q-Learning is reinforcement learning method. It learns an action-value (q-value) function for any finite Markov decision process used to find optimal policy for the agent. After it has learned the q-value function, it can follow the optimal strategy by choosing best q-value. ?citation? Algorithm is value iteration update for every observed state ?citation?:

$$Q_{t+1} \leftarrow Q_t(s_t, a_t) + \alpha \cdot (R_{t+1} + \gamma \cdot \max_a Q_t(s_{t+1}, a) - Q_t(s_t, a_t)) \quad (1)$$

where $Q_t(s_t, a_t)$ is old value, α is learning rate, R_{t+1} is reward after performing action a_t in state s_t , γ is discount factor and $\max_a Q_t(s_{t+1}, a)$ is maximum optimal future value.

0.1.3 Quoridor complexity

Estimated game state complexity was $3.9905 \cdot 10^{42}$ [Mertens (2006) (2)], however, this is very rough estimate, since it includes many states multiple times, since it counts with permutations instead of combinations of walls.

My approach with estimate will be similar. I will estimate maximum states of this game, which will include impossible states such as:

1. pawn in the winning position where it could not end due to walls
2. pawns not having the path to the winning position
3. walls crossing each other
4. pawn in the winning position and on turn

Moreover, this estimate will it count as a different state when different player is on the move and also different number of walls in players stocks. Both of these could make the game very different in the outcome.

S_p was corrected to not include both pawns in the winning positions. $f(i)$ stands for different wall counts in the stocks. 2 in $2 \cdot S_p \cdot S_f$ counts different players on turn.

Result is maximum number of states, which is significantly less then former estimate. However, even if I could evaluate

10^6 states in one second, it would take around $7.2172 \cdot 10^{13}$ years to evaluate this many states. Also, lets assume it takes on average 50B of memory per state. Then I would need approximately $1.138793 \cdot 10^{29}$ bytes of memory to store all states in the computer.

$$S_p = 81 \cdot 80 = 6480$$

$$S_f = \sum_{i=0}^{20} \prod_{j=0}^i (128 - 4j) = 6.1582 \cdot 10^{38}$$

$$S = S_p \cdot S_f = \mathbf{3.9905 \cdot 10^{42}} \quad (2)$$

$$S_p = 81 \cdot 80 - 9 \cdot 9 = 6399$$

$$f(i) = \begin{cases} i + 1 & \text{if } i \leq 10 \\ 21 - i & \text{if } i > 10 \end{cases} \quad (3)$$

$$S_f = \sum_{i=0}^{20} f(i) \binom{128}{i} = 1.7796 \cdot 10^{23}$$

$$S = 2 \cdot S_p \cdot S_f = \mathbf{2.2775866 \cdot 10^{27}}$$

0.1.4 Perceptron

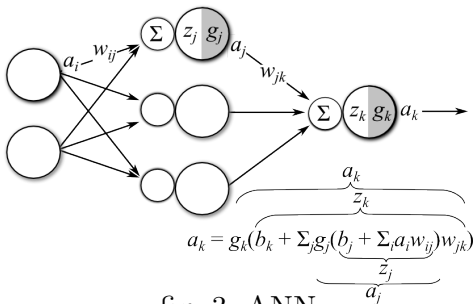


fig. 3: ANN

Artificial neural network (ANN) is a family of models inspired by biological neural networks used in computer science to approximate functions with large number of inputs. Generally, artificial neural network is presented as a system of interconnected neurons exchanging messages between each other. These connections have weights that can be adjusted based on experience which makes the network capable of learning.

Perceptron is an algorithm for supervised learning of binary classifiers where one neuron has multiple weighted inputs and single output. Single perceptron can learn to decide between two linearly separable classes. Multiple perceptrons in multiple layers (MLP) use arbitrary activation function which makes it able to perform classification or regression based on the activation function chosen.

References

P.J.C. Mertens. A quoridor-playing agent. Master's thesis, Maastricht University, June 2006. URL <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.134.5605&rep=rep1&type=pdf>.