UE Artificial Intelligence

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WS 2015

Filip Korzeniowski, Rainer Kelz

Department of Computational Perception
Johannes Kepler University
Linz, Austria

JOHANNES KEPLER UNIVERSITÄT LINZ

Department of Computational Perception

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Contents

- brief discussion of the last exercise sheet
- (very) brief discussion of the new exercise sheet
- Competition(s)
- Adversarial Search and Heuristics
- Monte Carlo Tree Search

Question 1

Single Linked Lists and Array Backed Lists

SLL Single Linked List

SLL,TP Single Linked List with Tail Pointer

ABL Array Backed List

ABL,$\neg S$ Array Backed List, when the space runs out

Average/Worst Case Runtimes:

Operation	SLL	SLL,TP	ABL	ABL,$\neg S$
Insert (end)	$O(n)$	$O(1)$	$O(1)$	$O(n)$
Contains	$O(n)$	$O(n)$	$O(n)$	$O(n)$

Question 1

Hash Tables (and Hash Sets)

HT Hash Table

Average/Worst Case Runtimes:

Operation	HT (average case)	HT (worst)
Insert	$O(1)$	$O(n)$
Contains	$O(1)$	$O(n)$

Question 2
Uninformed Search

- to keep track of **visited** nodes we use a HashSet / HashTable
- what would happen otherwise ?

Question 2

Uninformed Search - effects when using a Linked List / Array

- the number of leaves in a tree with branching factor *b* and depth *d* is $O(\mathrm{b}^d)$
- at search depth *d* we expand $O(b^{d+1})$ nodes in the worst case
- every time we visit a node, we put it into "`visited`", an operation which runs in $O(1)$ (if we have a tail pointer)
- at search depth *d* there are $O(b^d)$ nodes in this list!
- every time we expand a node, we call "`contains`", which will run in $O(b^d)$ *on average*!

Question 2

The average asymptotic runtime of BFS with a **naive** closed-list

- in (1), the $O(b^d)$ stems from the "contains"
- in (1), the $O(b^{d+1})$ is the number of nodes we expand

$$
\begin{aligned}
& O(\sum_{d=1}^{D} O(b^d) \cdot b^{d+1}) && (1) \\
= \quad & O(\sum_{d=1}^{D} b^d \cdot b^{d+1}) && (2) \\
= \quad & O(\sum_{d=1}^{D} b^{d+d+1}) && (3) \\
= \quad & O(\sum_{d=1}^{D} b^{2d+1}) && (4) \\
= \quad & O(\frac{b^3(b^{2D}-1)}{b^2-1}) && (5) \\
\sim \quad & O(b^{2D}) && (6)
\end{aligned}
$$

Question 2

The search-space is **given**!

- the search space is **given** to you by “`adjacent`”!
- changing this list **changes the search space**!
- a search algorithm is not **universal**, if you choose to **ignore whole branches** of the space **that you are given**!
- don’t change the space!

Question 3

Theoretical part

3C: Which of the heuristics guarantees that Greedy Best-First Search will lead to an optimal solution? Which of them guarantees obtaining an optimal solution using A* Search?

- Greedy Best-First Search **never guarantees** to find the optimal solution, no matter which heuristic.
- A* finds an optimal solution if the heuristic is **admissible**.
- **admissible** means always **underestimating** the true cost
- holds for both Euclidean and Manhattan distance in our case
- hence, **A* will find an optimal solution with both heuristics**.

Question 3
Theoretical part

3D: Which of the heuristics is better?

- a heuristic h_2 **dominates** h_1 if, for any node n, $h_2(n) \geq h_1(n)$
- if h_1, h_2 are admissible, and h_2 dominates h_1, A* with h_2 will never expand more nodes than with h_1
- for our problem, Manhattan and Euclidean distance are admissible
- $\forall \mathbf{x}, \mathbf{y} : d_{MH}(\mathbf{x}, \mathbf{y}) \geq d_{EC}(\mathbf{x}, \mathbf{y})$
- hence, **Manhattan distance is better** (for our problem)

Assignment 2

- implement MinMax and AlphaBeta
- reasoning via resolution, forward or backward chaining

General

How hard is it to make a **ZIP** file according to **detailed** specs?

- ... please hand in files according to specs?

Competition(s)

- the first round of (our) competition will start on 20.11.2015
- please upload your bot to MOODLE **before** 14:00 !

Competition(s)

- at the JKU LAN Party there will be a coding contest
  - http://informatik.jku.at/students/lan/2015ws/
  - https://github.com/coduno
- it'll involve writing an (intelligent) agent that plays a game
- as far as I know:
  - you'll not have access to the game-engine itself to do planning (as you have for this exercise)
  - it's going to be N bots in 1 arena
  - the branching factor will likely be enormous
- what you could do:
  - optimal path planning with A* (to walk around)
  - adversarial search to search through close encounters

JKULANXXL

WS 2015

50 Stunden non-stop
ab Freitag 13.11. 13:00 Uhr
JKU Managementzentrum EG

Coding Contest
Das weltweit erste Coduno Battle
Start: 13.11. ab 10:00 Uhr

Reservieren und Anmelden
forms.jku.at/oeh/lan2015

Adversarial Search

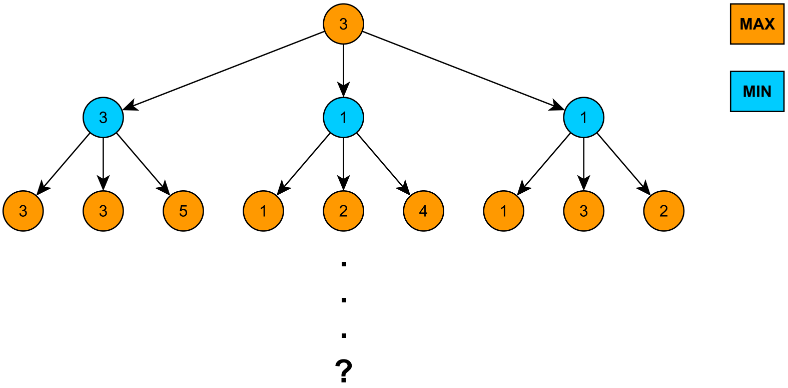
Problems

- the MinMax algorithm needs to generate the whole game tree
- this is intractable for any interesting game
- with AlphaBeta pruning we still have to progress all the way to the leaves of the game tree
- real games have time limits

Adversarial Search

Limiting the search depth

- cut off the search at a “reasonable” depth
- what is “reasonable”, depends on the nature of the game



Evaluation Heuristics

How do we get a score for an unfinished game?

- say we cut off the search at a “reasonable” depth
- how do we know what the value of the nodes are?
- we need to **assign a value** to all the nodes at this depth
- we need a **function** that judges **how favorable** the situation is for us, **at this particular point** in the game
- the **quality** of this function determines playing performance!

Evaluation Heuristics

Quality considerations - what should a heuristic look like?

A good heuristic should ...

- **order** the **terminal** states exactly as the **true utility function**
- be **quickly** evaluated
- be **correlated** with the **actual** chances of **winning**

Horizon effect

One can only plan for as far as one can see...

- say we search until a maximum depth of D ply
- we select our next move, m_D based upon the evaluation of all nodes at depth D
- if we would have continued to a search depth of $D + d$, we may have found a move m_{D+d} with $score(m_{D+d}) > score(m_D)$
- we couldn't look over the **horizon**, due to our limited computational budget

Quiescence Search

Continue searching in certain situations...

- we may have a **soft** and a **hard** depth limit
- in an “unstable” or “dangerous” situation we might choose to **continue** searching
- the idea is that our evaluation heuristic is **only applied** to nodes that are somehow “**quiet**”
- “quiet” nodes are those that are **unlikely to change in value** in the near future
- we need an additional function that judges the current **game dynamic**

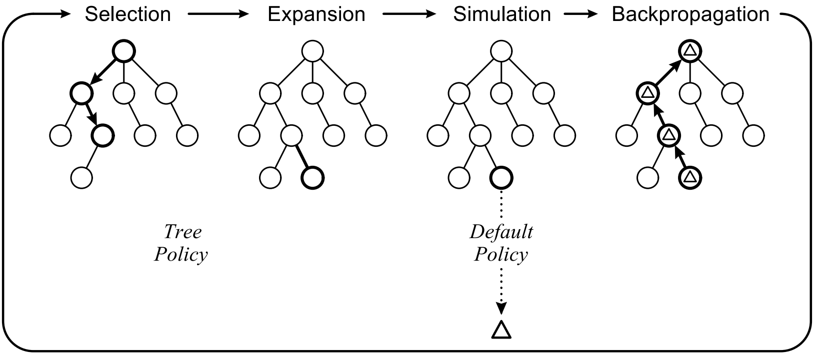
Monte Carlo Tree Search

Rolling the dice, repeatedly

- the basic idea is very simple: **play** a bunch of **random games**, from **start to finish**, to **obtain outcomes**
- we are **randomly sampling** paths through the state space
- choose the next move that resulted in a win **most often**

Monte Carlo Tree Search (taken from [1])

In four easy steps!



Monte Carlo Tree Search

A few random tidbits

- trivially parallelizable
- converges to minimax decision (with infinitely many samples)
- you can stop MCTS at any time and return the best move so far
- MCTS does not need domain specific knowledge
- plain MCTS may work for your problem domain “out of the box”

Questions

?

[1] Cameron B. Browne, Edward Powley, Daniel Whitehouse, Simon M. Lucas, Peter I. Cowling, Philipp Rohlfshagen, Stephen Tavener, Diego Perez, Spyridon Samothrakis, and Simon Colton. A Survey of Monte Carlo Tree Search Methods. *IEEE Transactions on Computational Intelligence and AI in Games*, 4(1):1–43, March 2012.