

Artificial Intelligence
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Lecture-35
Adversarial Search: Summary and Other Games-Part-7

So, summing up, they have been a lot of deterministic games where we have spent some of the today's lecture on chess. Some of the ideas are also valid in many other games.

(Refer Slide Time: 00:30)

Deterministic Games in Practice

- **Checkers:** Chinook ended 40-year-reign of human world champion Marion Tinsley in 1994. Used a precomputed endgame database defining perfect play for all positions involving 8 or fewer pieces on the board, a total of 444 billion positions. Checkers is now solved!
- **Chess:** Deep Blue defeated human world champion Garry Kasparov in a six-game match in 1997. Deep Blue searches 200 million positions per second, uses very sophisticated evaluation, and undisclosed methods for extending some lines of search up to 40 ply. Current programs are even better, if less historic!
- **Othello:** human champions refuse to compete against computers, who are too good.
- **Go:** until recently, human champions refused to compete against computers, who were too bad. In Go, $b > 300$, so most programs use pattern knowledge bases to suggest plausible moves, along with aggressive pruning. In 2016, DeepMind's AlphaGo defeated Lee Sedol to end the human reign.



Checkers, for example, is a one such game, where in 1994 machines defeated human champion, Chinook is the machine software. It defeated the 40 year reign of humans by defeating world champion in 94. It use a pre computed endgame database, and it evaluated a total of 444 billion positions. We consider checkers as now solved. Similarly, in chess, the blue defeated Garry Kasparov in 97.

It uses a combination of opening game end game mini max in the middle game, and undisclosed method for doing extending some lines of search using questions, search many different kinds of search sometimes it will go up to 40 depth. Typically it will go to 12 to 14 depth but some cases it will go to 40. That is a lot of depth. And because of that, it completely stumped Garry Kasparov at the time later, chess sprit software's have become so good that nobody no human wants to play chess with the machine.

The best player by the way are neither human nor machines the combination of humans and machines. So the world looks hope is that in the limit of things, humans and machines to be working together. Othello human champions do not compete against machines because machines are too good. Go was an oddity. It was an oddity because until 5 years ago, humans will not play against machines because machines were too bad.

I have been teaching the AI course for the last 5 6 7 years and earlier I used to say there is no hope that machine are going to defeat humans and go for a very long time.

(Refer Slide Time: 02:24)

Game of Go		
human champions refused to compete against computers, because software used to be <u>too bad</u> .		
	Chess	Go
Size of board	8 x 8	19 x 19
Average no. of moves per game	100	300
Avg branching factor per turn	35	235
Additional complexity		Players can pass



Why is that? This is because if you compare chess and go, chess is 8 cross 8 boards go is 19 cross 19 board forget universe playing it is just too big. In chess typically your game finishes in 100 moves in go it takes about 300 moves. The average branching factor in chess is 35 the average branching factor in go 235 if you really played this move, you will not be able to search beyond 3 or 4 depth typically.

And there many other additional complexities you know there are some people may start with some advantage in the beginning etc. The players cannot even pass I will not to play this game part you play the next game again, next tournament. So, in the game of go, humans were so good and machines was so bad that they will not compete. And suddenly and I would say suddenly, because by 2015 we had no idea. And in 2016 this had already happened.

Deep minds alpha go defeated Lee Sedol. To end the human Lee Sedol is considered to be the Federer of go, go is a more oriental game. So Chinese Japanese Korean players are the best players. I think Lee Sedol was Korean.

(Refer Slide Time: 03:38)

AlphaGo (2016)

- Combination of
 - Deep Neural Networks
 - Monte Carlo Tree Search
- More details later.



And it used a combination of deep neural networks and tree search but not of the mini max verity sampling with tree search so instead of going through the full sub tree, I will just sample a part of the sub tree and I will do it intelligently. And I will do it again and again. And that is called Monte Carlo search Monte Carlo is the sampling idea in the context of tree search. And typically I teach both of these. But in this class, I may end up teaching only one because of limited time.

(Refer Slide Time: 04:11)

Other Games

	deterministic	chance
perfect information	chess, checkers, go, othello	backgammon, monopoly
imperfect information	stratego	bridge, poker, scrabble



Now, of course, there are many other games. So some games are deterministic, and perfect information like chess in chess, I do not know anything more than my opponent. And everything has deterministic outcome, then there are games of chance, but everybody knows everything like monopoly. I am not saying it is an interesting game or it may or may not be but monopoly, you roll a die.

When you roll a die, there is chance but everybody knows how much money you have, whatever where your establishments are on the board, etc. Then there are games of imperfect information, but deterministic. For example everybody knows. Not everybody knows everything, but the game proceeds in deterministically. Then their games of chance, but important information likes poker.

In poker, you have some cards the other person has some cards; you know yours the other person knows there is nobody knows everything. But there is chance because you know, a new card may come out any which way, similarly for bridge initial board positions you do not know, may come out randomly. So there are different kinds of games. So very quickly, what happens if I have a game of chance, you know.

(Refer Slide Time: 05:23)

Games of Chance

- What about games that involve chance, such as
 - rolling dice
 - picking a card
- Use three kinds of nodes:
 - max nodes
 - min nodes
 - chance nodes

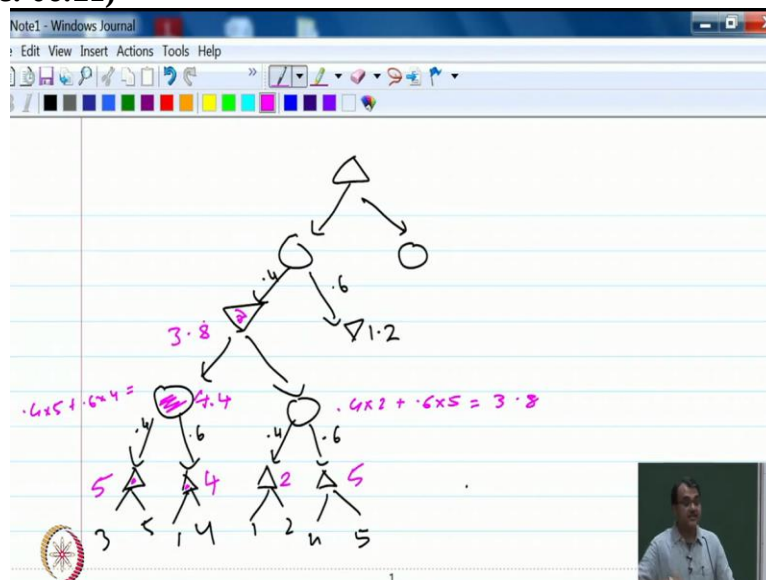


Life is not very different if I have a game of chance. So if I have a game of chance, what I need to do is that not only do I have a min and a max, I have a chance in the middle like I have a roll die and I have 6 different things that can happen. And so if you think about it, you will have a

max node you will have a min node but you will also have a chance node, which determined different things can happen with different probabilities and in your control will be the max node.

In opponents control will be the min node and in nature control will be the chance. So now you are playing a game against your opponent, but you know that nature is coming into the middle. And what you do there is you do not do mini max because you cannot, you have to figure out what to do with the chance node. So let us look at an example quickly and so in this example.

(Refer Slide Time: 06:21)



Let us say we are here. So, if we are here, in this node, what would the max node do 3 or 5, 5? Here the max will do 5 and here the max will do 4. So far, so good. But now, above it is a chance node, this left sub tree will happen the probability 0.4 and this right sub tree will happen to 0.6. So if I come to this node, what can I say, well, I cannot compute the best value because I should not compute the best value because it is not in my hand, I will not pick the left and get the best value.

In fact, random event will happen and so the best I can do is to take an expectation. And so my expected value at this node will be $0.4 \text{ into } 5 + 0.6 \text{ into } 4$. And that is 4.4. Let us do one other so this would be 2 this would be 5 and this expectation here would be $0.4 \text{ into } 2 + 0.6 \text{ into } 5$ which is 3.8. Now let us think about the min. So the min says min at this point, so the min says that I could go left and then random things will happen and adversary will play etc. And I will get 4.4.

I could go right, and then random things will happen in the adversary will play and I will get 3.8 and expectation which game should I play? I should go right because I am a minimizer. So I will get a 3.8. And this sort of keeps going up. Basically, that is the only change with respect to the mini max algorithm. And this algorithm is called expecti mini max.

(Refer Slide Time: 08:27)

Games of Chance Expectiminimax

chance node with
max children

$$\text{expectimax}(c) = \sum_i P(d_i) \max_{s \in S(c, d_i)} (\text{backed-up-value}(s))$$

$$\text{expectimin}(c') = \sum_i P(d_i) \min_{s \in S(c, d_i)} (\text{backed-up-value}(s))$$

And it is a general principle. Suppose I removed the adversary, they will become expecting max. If I remove the chance, it will become mini max. And if I have all me opponent and chance that will become expecti mini max, I have already done this example.

(Refer Slide Time: 08:43)

Complexity

- Instead of $O(b^m)$, it is $O(b^m n^m)$ where n is the number of chance outcomes.
- Since the complexity is higher (both time and space), we cannot search as deeply.
- Pruning algorithms may be applied.

And it is time complexity would be b to the m and n to the m because let us say I have n chance nodes at every point, and then my tree will have that much expansion. And then there are some imperfect information games. We will skip this.

(Refer Slide Time: 08:55)

Imperfect Information

- E.g. card games, where opponents' initial cards unknown
- Idea: For all deals consistent with what you can see
 - compute the minimax value of available actions for each of possible deals
 - compute the expected value over a





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Status of AI Game Players

• Tic Tac Toe – Tied for best player in world • Othello – Computer better than any human – Human champions now refuse to play computer • Scrabble – Maven beat world champions Joel Sherman and Matt Graham • Backgammon – 1992, Tesauro combines 3-ply search & neural networks (with 160 hidden units) yielding top-3 player • Bridge – Gib ranked among top players in the world	• Poker – 2015, Heads-up limit hold'em poker is solved • Checkers – 1994, Chinook ended 40-year reign of human champion Marion Tinsley • Chess – 1997, Deep Blue beat human champion Gary Kasparov in six-game match – Deep Blue searches 200M positions/second, up to 40 ply – Now looking at other applications (molecular dynamics, synthesis) • Go – 2016, Deepmind's AlphaGo defeated Lee Sedol – 2017, AlphaGo defeated Ke Jie
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So here is where we are. In a lot of the game say tic tac toe we are not better than the best human. We always draw. Othello we are good. Better than humans scrabble we beat human's backgammon we beat humans in 92 bridges we are ranked among top players in the world maybe we beat humans I need to check. Poker was a hard game. Poker was considered a hard game except in 2015.

University of Alberta showed that at least the heads up limit Hold'em poker is solved and it was solved again by huge amount of computation. Like months of you know cluster computation large cluster computation, which led to playing poker as good as humans and defeating humans. In checkers in 94, it was solved in chess in 97. We defeated humans and in go in 2017 we defeated the go champion 2016 we defeated Roger Federer, but you know, there was always Djokovic.

So that was Jay and from China I believe, and he was defeated in 2017 in go. In fact, I asked myself this question before this class, is there any game which is now the go of today? Like, you know 5years ago? It was go, go was the next frontier. Chess was solid go was too high. Now, that go chess champion, go champion has been defeated. What is the next game? dota, Nishanth say there is a game called dota it stands for you do not know.

It is a game but he does not know the full form. And apparently that is the next frontier. Maybe I do not know about it. Open AI is playing it. So maybe it is the next frontier, but at least I could not think of any. And so we will check out dota just to get a sense of you know what it is, maybe it is very hard. There are sort of these games; it is playing these very complicated video environments and so on so forth.

And you have to make a, you know, thing that kills people and you know, moves around it, possibly those that would be one of those but this this whole idea of board games, games, which are sort of formal games, which can be written in a formal specification, and so on so forth. I do not know what is the next frontier there?

(Refer Slide Time: 11:35)

Summary

- Games are fun to work on!
- They illustrate several important points about AI.
- Perfection is unattainable → must approximate.
- Game playing programs have shown the world what AI can do.



I think they are kind of this leads us to the end of the lecture on games. Games have been fun to work on for AI researchers you know, AI researchers are really interested in the they love games in general, people love games, and if you can play game for a living, that is a great life. They illustrate several important points about AI how to do search in a life depth. How do you cut off search? What do you do at the time of cut off what different techniques can use to extend search in a variable fashion, the idea of meta reasoning, how much to spend time here thinking.

And how much to spend time there thinking etc. it also exposes that perfection is unattainable. Optimality is a luxury, we always have to approximate and select is approximate but still get to a good solution and in a beat the next best thing that exists. That is an inside that we get from game playing. And game playing programs have traditionally shown the world what AI can do, and this is now changing, because now it is more about medical diagnosis now is more about using AI for this and that and the other.

But traditionally, games have been one vehicle by which AI researchers have demonstrated the success in the field. So we will stop here thanks.