Resistance Project Report

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Introduction

"The Resistance" is a board game for five to ten players with hidden identities in which the subset of nominated players are despatched on missions. Depending on the identity of the player, they will either sabotage the mission or successfully complete the mission. Due to the incomplete informational nature of the game, it is a great undertaking to enforce an AI agent for it. Various strategies, such as the Bayes rule, Monte Carlo tree search, and various expert rules, have been explored to expand a sophisticated agent. It grew to become out that the high-quality strategies for the sellers had been those who carried out the Bayes rule and the look for Monte Carlo.

Literature review

Bayes Rule

An accurate agent will collect as much information from the environment as feasible and take movements primarily based totally on that information. However, for a game with hidden facts like the Resistance, the collected information by the agent itself may not sufficient to make a decision because the genuine state of the game is truly unidentifiable. Therefore, a good agent should bear in mind numerous occurrences and their likelihood to make the proper decision. Bayesian probability has long been researched withinside the discipline of artificial intelligence, while is far essential to the purpose under uncertainty (Poole & Mackworth 2010). In Bayesian probability, the probability is taken into consideration a perception approximately a certain occasion taking place withinside the future or a declaration to be genuine, primarily based totally on historical observations. (Poole & Mackworth 2010).

Base on the Bayes' Theorem formula, the probability of H conditional on E is defined as

$$\mathbf{P}_E(H) = [\mathbf{P}(H)/\mathbf{P}(E)]\ \mathbf{P}_H(E)$$

supplied that each phrase of this ratio exists and $\mathbf{P}(E) > 0$ (Joyce, 2016).

H is the proposition of a few forms of utterance, whilst *E* represents the records found by the agent. $\mathbf{P}_E(H)$ is the posterior opportunity of proposition *H*, i.e. the persuasion agent A in proposition *H*, given all the history E it has observed (Poole & Mackworth 2010).

Given the example from Joyce (2016), about 2.4 million of the 275 million Americans alive on January 1, 200 died during the 2000 calendar year and roughly 1.36 million of the 16.6 million senior citizens (age greater or equal than 75). The unconditional probability of the hypothesis that a randomly chose American A died during 2000, *H*, is just the death rate at the population level $\mathbf{P}(H)$ = 2.4M / 275M = 0.00873 and the probability of *A* death conditional on the information *E*, that *A* was a senior citizen, we divide the probability that *A* was a senior who died, which is $\mathbf{P}_H(E)$ =

1.36M / 275M = 0.00495, by the probability that *A* was a senior citizen, $\mathbf{P}(E)$= 16.6M / 275M = 0.06036. The probability of *A* death given he/she was senior is $\mathbf{P}_E(H) = [\mathbf{P}(H)/\mathbf{P}(E)]\ \mathbf{P}_H(E)$ = 0.0873/0.06036 * 0.00495 = 0.007159.

Monte Carlo Tree Search (MCTS)

Monte Carlo Tree Search is a method of finding optimal decisions in a given area by taking random samples in the decision space and building a search tree based on the results. It has already had a profound impact on artificial intelligence approaches to areas that can be represented as sequential decision trees, especially games and planning issues (Cameron, Edward, etc, 2012). For Monte Carlo Tree Search, the search tree is incomplete, so the MCTS method is used to expand the tree by randomly selecting decisions/unvisited nodes to expand (Taylor 2014).

In fact, the MACTS process consists of selection, expansion, simulation, and back-propagation phases to try to achieve the expected utility of the selected state (Taylor 2014). For each iteration of the algorithm, the tree policy is used to find the most urgent node/unvisited nodes in the current tree. Tree policies seek to balance exploration (searching for areas that have not been well sampled) and exploitation consideration (searching for areas that appear promising). A simulation is then performed of the selected nodes and the search tree is updated based on the results. This involves adding child nodes that correspond to the actions taken by the selected node and updating its ancestors. Movements are performed during this simulation according to predetermined policy, for example, performing uniform random movements.

According to Cameron, Edward, etc, (2012), The most advantage of MCTS is that intermediate state values do not have to be evaluated, such as a finite depth minimax search, which greatly reduces the amount of domain knowledge required. Only the terminal state values are required at the end of each simulation. Although the core algorithm has been shown to be effective for a wide range of problems, the full benefits of MCTS are still not exploited until it is adapted to suit the domain in question.

Selected Technique

Bayes Rule

The Resistance has a high degree of uncertainty because there are many game actions that do not provide solid information, such as proposals, voting, and the spy letting the mission succeed. Only mission failure can provide explicit information since resistances cannot betray the mission. The reason why choosing Bayesian probability is that this game is a non-deterministic game with an incomplete set of information from which the true state of the game can only be deduced, without actually being determined. The behaviour of other players would affect the outcome of the game, creating more uncertainty. Therefore, the ability of Bayesian probability to reason in uncertainty can be used in the context of the Resistance. As the game progress, more and more sightings are obtained, this gives the agent playing that game a perfect opportunity to use this new sighting to draw a conclusion about the true state of the game. Later decisions can be made on this basis.

Implementation

Firstly, we need to list all the possible spies combinations based on the game players number, then map each list with an initial suspicion value

$$P(c) = \frac{1}{numberOfCombinations}$$

This suspicion probability will be updated during the entire game. When an action *a* has occurred, we need to estimate the probability of this action occurring to each combination, which gives P(*a* | *c*). Then we need to accumulated the overall probability for each combination affected by action *a* occurrence.

$$\sum^{\prime} P(a \mid c')P(c')$$

Since we know that the action a has occurred, we can update all of the P(*c*) suspicions with the value of P(*c* | *a*) for that combination. We can update from this in each step in-game. Therefore, based on the Bayes' theorem,

$$p(c \mid a) = \frac{P(a \mid c) \cdot P(c)}{P(a)}$$

The accuracy of our possibility values relies upon how we calculate **P**(*a* | *c*) for every kind of action. It's extraordinarily sincere to estimate **P**(*a* | *c*) for assignment effects due to the fact we handiest want to recall the spies at the team, and spies have ideal expertise. It's extra hard to estimate **P**(*a* | *c*) for nominations, votes, and assignment effects in view that we are thinking about resistance gamers and spies at the equal time. In those cases, I determined to apply the belief that each gamer has ideal expertise. This isn't a complete version of behaviour, however, it is straightforward to calculate and it does not contradict any expertise that a participant might have in that world. A secret agent will make a choice the usage of ideal expertise. Any moves towards the most beneficial secret agent method could be diagnosed as extra resistance-like. As such, it permits us to comparison secret agent-like behaviour and resistance-like behaviour.

A secret agent participant desires to recollect one of a kind possibility values. As with a resistance participant, they want to recollect the possibility of a challenge succeeding from a resistance participant's factor of view. They additionally want to recollect the possibility of a challenge failing given their know-how of who the spies are. To minimise the number of records that the resistance gamers get from the challenge result, they ought to purpose for a perfect wide variety of fails. That is, if the challenge calls for fails, they ought to maximise the hazard of precise spies gambling fail cards. By multiplying those possibility values together, the crew with the best rating might be a crew that appears suitable to resistance gamers and has an excessive hazard of failing.

We are able to conduct voting selections with the help of evaluating the likelihood of fulfilment for the nominated group with equal probability of success for all the vital teams. If the ratio is above a certain threshold (assumed the average of suspicion of all possible mission teams), the resistance players must reject since the current mission team suspicion is higher than the average of all suspicion. If the ratio is below this threshold, the resistance players can agree to vote. If spies are careful as well, they should also consider this way. The spy must choose in a high-quality way to achieve win if the mission team has enough minimum required spies, then the spies group must approve, in other cases must reject except the last proposal or last mission to end this game which the secret information is no longer important.

Validation

To test the performance of my agent code, and with the number of players increasing, the time run is increasing as well, therefore, I ran my agent from five to ten player count in 1000 respectively. The result shows below:

Player Count	Spy Wins	Res Win	Spy win ratio	Res win ratio
5	607	393	60.7%	39.3%
6	561	439	56.1%	43.9%
7	713	287	62.92%	37.08%
8	626	374	62.6%	37.4%
9	559	441	55.9%	44.1%
10	634	366	63.4%	36.6%

In general, the resistance winning probability is relatively lower than the spy winning. That winning ratio between spy and resistance is roughly 6:4 when the game play number closing to 10000 times.

References

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