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CS 4710: Homework 3

Negotiating Agents

**Agent 1:** rv5rr.py

**Goal:** For this agent, we set out with the intention to determine the opponent’s optimal ordering. With this knowledge, we hoped to find the perfect compromise between the two agents, so that both would gain some (hopefully equivalent) utility.

**Approach**: This agent starts by figuring out all of the different possible permutations of the given preferences list. It also figures out the different utility[[1]](#footnote-1) each permutation provides to itself. As we were programming, we realized that the utility was a function of the Hamming distance of an agent’s perfect ordering to the offer it received. As such, there were a fairly limited number of levels of utility, which will be referred to as “utility buckets” in the rest of this description. We created a dictionary that mapped each utility bucket to a list of offers that would give the agent that utility.

Next came the challenge of figuring out what the opponent’s preference was, and using that to find a compromise. We decided to create a weighted average of each object’s location in each offer, with offers that gave the opponent higher utility weighted to have more of an effect in calculating the object’s real location. After weighting these averages, we set the value with the lowest position calculation as the first element, the next lowest as the second element, and so on until we had an ordering that could potentially be the opponent’s preference. We then passed this ordering as an offer to a function (find\_highest) to find out what our best compromise was.

The find\_highest function would cycle through each utility bucket and search for an offer that had the smallest Hamming distance between what we had calculated to be the opponent’s preference and each potential offer in the utility buckets. In order to make sure we were not losing out and giving the opponent exactly what they wanted, the find\_highest function also took in another parameter called bucket\_num. This parameter limited how many of the utility buckets to go through, and the search always started with our agent’s highest utility bucket. This bucket\_num was adjusted based on the opponent’s actions. If the opponent decided to make an offer that gave them higher utility than a previous offer, we would decrease bucket\_num[[2]](#footnote-2). This meant we would search through one less lower utility bucket, meaning we were less compromising[[3]](#footnote-3). Similarly, if the opponent gave us a successive offer that gave them the same utility as their last offer, we would not change the number of utility buckets we searched through. Lastly, if the opponent was compromising and gave us an offer that left them with less utility than before, we would increase the number of buckets we searched through.

**Results:** We ran our tests against a few other agents we had that were in their beginning stages. These were agents we had either started making and decided not to use, or snapshots of early phases of our working agents. One of the agents was the provided random agent. To test, we ran our agent against the same opponent for 3 consecutive negotiations with the same scenario for each negotiation. This happened twice for each scenario; once, the agent was negotiator A for three rounds, and then the agent was negotiator B for three rounds. The results of these tests are listed below, with the table showing our agents utility (rounded to two digits after the decimal), followed by a slash and then the opponent’s utility (rounded to two digits after the decimal point).



Against a negotiator that accepts offers that meet a certain threshold for utility. This threshold starts at the maximum utility and decreases at every round.



Against a negotiator that mimics its opponent’s relative movement in terms of utility.



**Agent 2:** dma3fq.py  
  
**Approach:** For our second agent, we decided to develop an incrementally more elaborate system. The benefit here was twofold, we were easily able to expand from the different points of our development as ideas struck, and we had a series of working agents to test against, to see if our changes were helping us improve relative to them. Initially, we built an agent that was quite simple, it simply enumerated all possible permutations of the list, then categorized them by how much utility each one was worth, and then determined how many different levels of utility there were. We consider most of the problem from the perspective of moving “up” or “down” in these levels, which is roughly the same as making an offer with more or less utility respectively. To start, the agent had a minimum utility it needed to achieve. This minimum decreases as the rounds go on, and if at any point it receives an offer of greater utility than the one it is currently on, it accepts. Obviously, this isn’t very complicated, and it is very easy for a system to beat, by holding out and making offers that are bad for the agent until the very end, then making a single offer that is reasonable for our agent and great for theirs.

To improve on this, we decided to add a simple predictive scheme to the agent. The agent keeps track of what the opponent has done in their moves so far, how many times they’ve increased their own utility, how many times they have conceded utility, and how many times they haven’t changed. It uses this information to determine the likelihood of the opponent taking a loss to utility, which is assumed as being a sign of cooperation. Strictly speaking, it might not always be, but it is assumed for the purposes of the agent that any decrease in utility is a sign of good faith. If the opponent is likely to cooperate, our agent cooperates by taking a hit to utility in our offer. If their agent is likely to drive their utility higher, ours will match them by sending a deal with a higher utility for us. The benefit to this approach is that it won’t fall victim to the mistakes of the first approach, it will tend to be tough with tough opponents and cooperative with cooperative opponents.

Our final approach, what we actually submitted as Agent 2, is a slight but important refinement on the probabilistic technique of its predecessor. Rather than constantly moving in the direction the opponent is most likely to move, it moves randomly up, down, or not at all, with the same likelihood that the opponent will impact their own utility the same way. In this way, it doesn’t fall into lowering its minimum utility with a cooperating opponent, then continuing to do so while the opponent is uncharacteristically uncooperative. The agent might move up or down, or even stay at the same amount of utility, even if opponent is cooperating or stonewalling negotiations, which allows for some variability and makes our agent more resistant to changes in the behavior of the opponent. This is additionally beneficial because it makes it harder for an opponent to read the strategy of the agent and exploit it.   
  
**Results:** We ran our agent against a few others that we had available, to see how it stood up to their strategies. To test, we ran it in 3 rounds of 10 iterations each as negotiator A, then the same as negotiator B. We did this for 3 different scenarios, but kept the scenario consistent for any set of 3 rounds. The results of these tests are listed below, with the table showing our agents utility, followed by a slash and then the opponent’s utility  
  
Against the fully random agent that was given: - negotiator.py

|  |  |  |  |
| --- | --- | --- | --- |
| As A | Input Size 5 | Input Size 7 | Input Size 9 |
| Round 1 | **7.42**/-.58 | **18.15**/-3.85 | -9/-9 |
| Round 2 | **7.42**/3.42 | -7/-7 | **23.46**/7.46 |
| Round 3 | 5.42/5.42 | **16.15**/-3.85 | **17.46**/13.46 |
| Final | **20.25**/8.25 | **27.3**/-14.7 | **31.92**/11.92 |

|  |  |  |  |
| --- | --- | --- | --- |
| As B | Input Size 5 | Input Size 7 | Input Size 9 |
| Round 1 | 5.42/5.42 | -7/-7 | 23.46/9.46 |
| Round 2 | 11.42/3.42 | 16.15/-3.85 | -9/-9 |
| Round 3 | -5/-5 | 16.15/-3.85 | 23.46/7.46 |
| Final | 13.83/3.83 | 25.3/-14.7 | 37.92/7.92 |

Against the agent that looks for a minimum utility decreasing over time: - simple\_negotiator (starts offering highest utility and slowly goes down. if the opponent beats threshold for “minimum” it accepts)

|  |  |  |  |
| --- | --- | --- | --- |
| As A | Input Size 5 | Input Size 7 | Input Size 9 |
| Round 1 | 9.42/5.42 | 8.15/0.15 | -9/-9 |
| Round 2 | 3.42/5.42 | 4.15/4.15 | -9/-9 |
| Round 3 | 7.42/5.42 | 2.15/2.15 | 15.46/11.46 |
| Final | 20.25/16.25 | 14.45/6.45 | -2.54/-6.54 |

|  |  |  |  |
| --- | --- | --- | --- |
| As B | Input Size 5 | Input Size 7 | Input Size 9 |
| Round 1 | 7.42/3.42 | 8.15/2.15 | -9/-9 |
| Round 2 | 9.42/3.42 | 8.15/-1.85 | -9/-9 |
| Round 3 | 7.42/1.42 | 8.15/-1.85 | 9.46/-6.54 |
| Final | 24.25/8.25 | 18.45/4.45 | -8.54/-24.54 |

Against the agent that determines the opponent’s probable move and matches it: - negotiator\_prob.py reads opponent’s move and copies it

|  |  |  |  |
| --- | --- | --- | --- |
| As A | Input Size 5 | Input Size 7 | Input Size 9 |
| Round 1 | 9.41/5.41 | 6.15/4.15 | -9/-9 |
| Round 2 | 5.41/7.41 | 10.15/2.15 | 11.46/13.46 |
| Round 3 | 5.41/7.41 | 8.15/2.15 | 11.46/13.46 |
| Final | 20.25/20.25 | 24.45/8.45 | 13.92/17.92 |

|  |  |  |  |
| --- | --- | --- | --- |
| As B | Input Size 5 | Input Size 7 | Input Size 9 |
| Round 1 | 3.41/7.41 | 10.15/-1.85 | 9.46/9.46 |
| Round 2 | 7.41/7.41 | 8.15/.15 | 11.46/9.46 |
| Round 3 | 5.41/3.41 | 2.15/4.15 | 13.46/15.46 |
| Final | 16.25/18.25 | 20.45/2.45 | 34.38/34.38 |

From the above, we can draw many interesting conclusions about the success of our bot. First, and perhaps most important, it tends to win. If the final results for each set of input files are summed, our bot gets more utility by far than the opponents. It does particularly well on the input file of size 7, never losing a single match up on that file. This could be just because of the size, it might be a “sweet spot” of available options, enough range for the bot to select mutually beneficial options without conceding too much. Another important takeaway is that overall the bot managed to come to mutually beneficial agreements. While it didn’t win every time, it never got negative utility out of a matchup. This is very important, as non-cooperative agents will tend to get big payoffs sometimes, but will also occasionally fail and pay the penalty. By avoiding that penalty, we hope our agent will have a better overall score than others.

It isn’t terribly surprising, but it is important to note that going first or second has no noticeable difference on the scores. This is good in that the agent doesn’t rely on going first or second, which is not something that is within our control. This removes one limitation on our code. There is a significant issue in how we calculate the available options to send as offers. The agent calculates every possible permutation of the items list, which grows very rapidly. Consequently any list of longer than about 11 items takes far too long to evaluate to be practical.   
  
**Future Improvements:** Based in part on the results of our tests, we had several ideas for how to expand on the agent that might help it beat certain opponents. We considered categorizing the data by the situations of the agent, for example, storing the probability of the opponent making an offer than increases their utility given that we increased ours on the last offer. Storing the information in such a way would probably look a bit like a Bayesian network, growing more complex depending on how many factors we consider as we collect information. We didn’t have time to implement this, but we believe it would allow us to make more accurate predictions about what our opponent will do, which in theory would allow us to better react.

**Important Note**: Both of these agents made use of Python’s itertool’s library’s permutation method. Since finding permutations is an exponential function, we decided to see how big a difference the number of elements for which we attempted to find a permutation made. The result can be seen in this graph:

From the chart, it is clear that there is a jump at the 10 - element mark. We attempted to find the time it would take for more elements, but unfortunately received a memory error. Given this finding, neither of the agents would work if given elements of size greater than 10 with the given time constraint of 30 seconds, assuming there was enough memory to store the various permutations (which we recognize may not be the case).

1. Since the utilities were given as a floating point number, and since it is not possible for floating point numbers to represent all numbers, we knew that we would get some numbers of identical utility that would be represented differently. To account for this, we decided to round off all floating point numbers at 5 decimal places, hoping to reduce the effects inherent in floating point arithmetic. [↑](#footnote-ref-1)
2. It is possible to get negative buckets here. This can occur if the opponent makes successive offers that increase their own utility. If this happens, the function only searches through its highest bucket (which yields this agent’s preference). The consequence to the opponent, however, is that they must make up the difference by offering successively lower utility offers so that our agent is more compromising by searching through more buckets. [↑](#footnote-ref-2)
3. At any point, it was possible that by going to a different bucket, we would find a perfect match for what we thought was their preference. To prevent the opponent from getting more utility than we were getting by searching in a lower bucket, we would only ever return, at best, an offer that had two items switched for the opponent. The only exception to this rule was if they offered something that was our best preference. [↑](#footnote-ref-3)