AASMA PROJECT PROPOSAL

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Keywords

multi-agent systems, gamification, dynamic epistemic logic, bayesian network.

1.1 Problem Definition

Multi-agent Systems have been contributing successfully to the development of complex distributed systems. Multi-agent systems are systems composed of multiple interacting computing elements, known as agents. [1] Agents are computer systems that are capable of deciding for themselves what they need to do in order to satisfy their objectives [1]. The multi-agent system that we intend to model is a knowledge game called *Cluedo* or *Clue*. The purpose of the game is to solve a murder by finding who the murderer was, what weapon was used and in which room the murder was committed.

The game is played on a board with a picture of the full house including all the divisions and the paths leading to each division. The game also includes cards of three categories: the guests, the weapons and the divisions; a pair of dices that are used to move each player over the board and pawns that represent each player.

Before the game beings, one guest card, one weapon card and one division card are blindly drawn from the three categories of cards and placed in an envelope in the center of the board. The categories are, then, shuffled all together into one deck of cards and evenly dealt to the players. Additionally, each player must pick a pawn that has a specific color and represents a specific guest.

The game begins with one player throwing the dices and walking over the board. The purpose is to move the pawn in order to reach one division so that a suspicion can be thrown. A suspicion consists of voicing a particular guest, weapon and division. The suspected division needs to correspond to the division the player landed upon. As the suspicion is voiced, the pawn corresponding to the suspected guest must be placed in that suspected division. The remaining players need to respond to the suspicion, in a clockwise order, by showing only one card corresponding to the suspected ones and only to the person that said the suspicion. If a player does not have any of the requested cards, the turn goes to the next player. If a card is shown, no further responses may be gathered.

To win the game, a player must place an accusation, and this can be done in any division. Each player can only make an accusation once in the game. However, now the accusation is not voiced but written. The accusing player checks the envelope, without showing it to the others, and if it is correct the player wins the game. If the accusation is not correct, the player has lost but the game continues. The losing player cannot play anymore but still needs to show the cards when other players voice a suspicion.

1.2 Relevance

Our specific problem is relevant to the real-world as it follows the same process as modern surveillance systems. Similarly, a Bayesian Network approach can be applied to determine the optimal movements of sensors in an environment in order to collect evidences from unknown targets and improve inference of unknown features.

2. SYSTEM PROPOSAL

The *Cluedo* game involves interaction of different players that results in complex knowledge changes. The game actions in *Cluedo* influence the knowledge states of the players. Our main purpose is to give account of how an agent's information changes due to actions.

In a multi-agent system, agents can learn information based on the actions of other agents. We intend to explore this by using a **Dynamic Epistemic Logic**. Dynamic Epistemic Logic is the logic of changing knowledge due to communication. [2] Our purpose is to combine logic with **probabilities** in order to reach new conclusions without having to see only the cards of other players. For example, player B voiced a suspicion "Scarlett with the gun in the kitchen" and player C has Scarlett. Then, player A shows a card to player B, therefore, player C knows that player A either has the gun or the kitchen, so there is 50% chance of being one or the other. We intend to pursue this strategy as it is an optimal strategy to win the game.

Another concern to keep in mind is a decision problem where the optimal path to move over the board is based on the expected utility of the observations. We intend to combine a **Bayesian Network** approach with a Dynamic Epistemic Logic so that each player can plan his motions according to the evidence acquired (directly or indirectly) and the evidence that needs to be collected to improve inference of unknown evidence.

In conclusion, we intend to have a multi-agent system where there is **communication** between agents. Each agent is **autonomous** and **deliberative**. Furthermore, we will implement a **predicate task specification** approach in which a utility is specified in terms of whether or not a predicate is satisfied (e.g., a player having one of the suspected cards). Agents will also be **open minded** agents where if there is a new intention the agent can change his intention (e.g., a suspicion is voiced so the agent's intention to go to a specific division or voice a specific suspicion can change). To make it a real-life environment, agents will have different **profiles**. Some can be bold, some can be cautions, some can be in between. In order to define these, we will provide probabilities for each agent. If the probability is reached, the agent can throw an accusation and possibly win or lose the game. The bold agent will have a lower probability than the cautions agent.

The environment will be a n*n square that will represent the board game containing the divisions and the paths leading to each division.

2.1 Research questions

With the previous problem analysis in mind, we define the following research questions:

Do different strategies affect the efficiency in winning the game?

Do different agent personalities change the behavior of the agent and his ability to win the game?

2.2 System evaluation

We intend to use two metrics to evaluate our system: different agent profiles and different game strategies. We aim to run simulations with different profile combinations in order to study the impact of: i) using Bayesian Networks to collect evidence, and ii) deliberative ability. We also aim to run simulations with different approaches such as using a Dynamic Epistemic Logic approach and using a naïve approach in order to study the impact of: i) common and distributed knowledge among the players, ii) deliberative ability, and ii) efficiency in winning the game.

3.1 Environment properties

Inaccessible
Nondeterministic
Dynamic
Discrete
Non episodic

The environment is inaccessible since agents don't have access to the cards of other agents. The environment is nondeterministic since agents execute their actions sequentially. The environment is dynamic since the world changes throughout the game. The environment is discrete since there are fixed number of pawns, cards, and possible moves. The environment is non episodic since the present state is dependent on previous ones.

3.2 Agent properties

Effectors: Each agent can move horizontally and vertically in the board game and enter each division.

Sensors: Agents have cards that are showed when a suspicion is voiced.

Autonomous	Yes
Adaptive	Yes
Rational	Yes
Curious	Yes
Reactive	No
Proactive	Yes
Sociable	Yes
Collaborative	Yes
Believable	No
Mobility	Yes
Personality	Yes
Veracity	No

Agents are autonomous since they have the ability to independently determine how to achieve their goals. They are adaptive since they have internal states and are able to learn from the action of others, thus, are not reactive. They are rational since they plan their motions according to the evidence acquired (directly or indirectly) and the evidence that needs to be collected. They are curious since they show interest in learning new information by making suspicions. Since there is communication between agents, they are sociable and collaborative as they need each other in order to accomplish their goals or to achieve them more efficiently. Agents are not believable and there is no veracity since we assume truthfulness in the game. Agents are able to move over the board, therefore, they have mobility and are proactive. Each agent will have a different personality as explained previously.

4.1. Research and Planning

Before starting the implementation, we had to research and gain knowledge on some key components: Multi-agent Systems, Dynamic Epistemic Logic and Bayesian Network. After, we had to think on how to tie all these components together in a game perspective where agents are able to perform problem solving, evaluation and prediction. After planning, we evaluated the different programming languages and decided to implement our solution in *Python* since it is substantially versatile and has many useful packages. Two *Python* we used were: *pandas* and *matplotlib* since these made it easier to manipulate and visualize data.

4.2. Simplifications

The *Cluedo* game involves many small details that we did not find relevant for the implementation such as rolling the dices to move the pawns and having secret passages. Therefore, in our implementation, we allowed each player to move directly to the division he wanted without having to roll dices as this would not add any additional information for our analysis. Furthermore, in our implementation, when an accusation is placed, the game ends whether the player won or lost so that we could analyze properly the behavior of bold agents.

5. IMPLEMENTATION

5.1. Structure

The implementation involves three main structures: the card, the player and the game. The card structure only contains two elements: the category of card (e.g., suspect, weapon, and division) and the name of the card (e.g., Miss Scarlett). The game structure is the environment representation and the player structure is the agent representation. In terms of knowledge, the game structure would represent the common knowledge shared among players (e.g., when a suspicion is made or knowing a player showed a card to another player but not knowing which card), whereas the player structure would represent the distributed and not common knowledge between two players (e.g., when a player shows a card to another player). This way we make a differentiation between common and distributed knowledge.

5.2. Game Initialization

The environment is represented in the game structure as a 7x7 board game that contains the initial positions for 6 players and the positions of 9 divisions. Furthermore, there are three metrics that can be changed in each game: number of players, number of bold/cautious players and different game strategies (e.g., Dynamic Epistemic Logic approach and naïve approach). These will influence the dynamic of the game and the behavior of players.

In the beginning, a Game instance is created. This game instance will then initialize the 21 cards and pick randomly three cards from the three categories (i.e., the crime cards). After, the number of players playing, their personalities and strategy used are picked by the user. The players are initialized by attributing an index for each player, and then, all cards in the game (except the crime cards) are evenly distributing among the players. Each player is attributing an initial position in the game and a personality.

Before the game starts, the probability tables for each player are initialized and folders with the index of each player are created in the directory of the project.

5.3. Player Initialization

The Player Structure is where the logic and behavior of an agent is defined. The decision making of each player is based on two main components: probability tables and utilities. However, the update on these components will change according to the strategy used and personality of the agent. There are two game strategies that can be used: Dynamic Epistemic Logic approach and naïve approach; and two agent personalities: bold and cautious.

A player is initialized with an index (i.e., the number/name of the player), cards, an initial position and a personality.

The initialization of the probability tables is done by creating three probability tables, one for each category. The columns of each table represent the card names for that category (not including the cards that the player already has), and the rows are the remaining players in the game (not including the player itself). Initially each value in these probability tables is empty as no knowledge has been gained.

Furthermore, each player also uses a **predicate task specification** approach in which utilities represent each card in the game. These utilities are initialized with either a 0 or a 1, depending whether the player has or not a card. If the player has a card the utility starts with 0 and if the player does not have a card the utility starts with 1. The utility represents the chance of a card being the crime card and is used to determine the optimal path to move over the board and the optimal suspicion that should be voiced. The utilities are based on the evidence acquired and the evidence that needs to be collected to improve inference of unknown evidence.

5.4. Game Start

5.4.1. Suspicion

The game begins with a player moving to a division and voicing a suspicion. To voice a suspicion, a player must pick three cards from the three categories and this suspicion is based on the utilities. For this, each player must check the reward that maximizes his play. For instance, for the suspect and weapon category, the player must pick a card that has the highest utility value as it represents a card in which he has no concrete evidence of. For the division category, the player must check the reward that maximizes his play by calculating the utility value minus the distance of the pawn to that division. The reason behind this is that a suspicion can only be made is the player is in the same division as the one being voiced.

5.4.2. Strategies

As mentioned previously there are two different strategies: a Dynamic Epistemic Logic approach and a Naïve approach. Using a **Dynamic approach**, players can learn information and gain knowledge based on three actions: when a **player shows us a card**, when a **player shows a card to another player** and when a **player shows no card**. Using a **Naïve approach**, players can only learn information and gain knowledge when a **player shows us a card**.

5.4.2.1. Player shows us a card

If a player has one of the voiced cards in the suspicion, shows it to the player that voiced the suspicion. The player that sees the card knows that the card seen is not one of the crime card, thus, can update his probability tables and utilities accordingly. The player removes the column corresponding to that card from the probability table (shown in Tables 1 and 2) and changes the utility of that card to 0 (shown in Figures 1 and 2).

	Wrench	Revolver	Rope	Lead Pipe	Candlestick
player1					
player2					
player3					
player4					
player6					

Table 1 – Probability table before card is seen.

	Wrench	Revolver	Rope	Lead Pipe
player1				
player2				
player3				
player4				
player6				

Table 2 – Probability table after card is seen. Player received the Candlestick card.

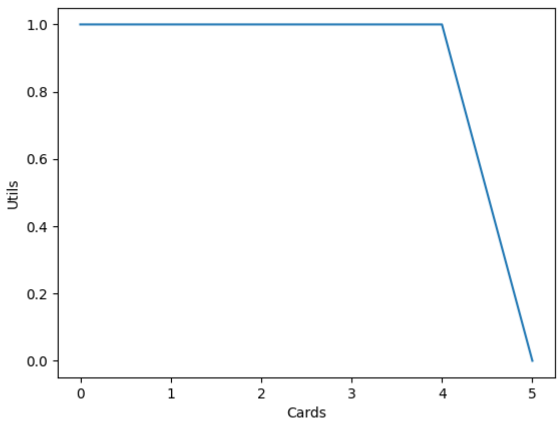

Figure 1 – Utilities graph before card is seen.

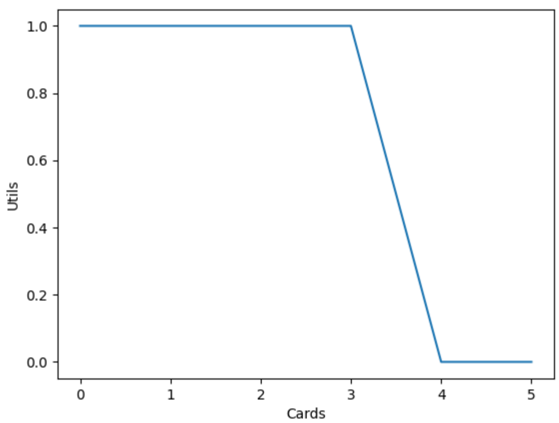

Figure 2 – Utilities graph after card is seen (e.g., card 4 is seen).

Furthermore, each player also saves the card that was found. The reason behind this is that if the number of different cards found from a specific player matches the total number each player must have, then that means the player does not have the remaining cards in the game. This way, players can gain additional knowledge by updating their probability tables.

5.4.3. Dynamic Approach

5.4.3.1. Player shows a card to another player

When a player shows a card to another player, even though we cannot see that card, we can still learn information and gain knowledge. There are three ways in which a player can learn information without having to see a card: when the player has/knows none of the cards voiced, when the player has/knows one of the cards voiced, and when the player has/knows two of the cards voiced. A player must check his probability tables to confirm if he knows any information regarding the cards voiced in the suspicion. However, if one of the cards voiced has already been showed to me by that same player, then I now must check the cards I have and not the ones I know. The reason behind this is that, for instance, if a player showed a card to me and in the next suspicion he shows that same card to another player, since I already have information about that card I would assume that the player now has one of the other two cards which might not be true. Therefore, if a player already showed of these cards to me, I must check the cards I have, otherwise, I must check my probability tables.

If I have/know none of the cards voiced, then there is 1/3 chance of the player having one of the cards voiced. If I have/know one of the cards voiced, then there is 1/2 chance of the player having one of the cards voiced (excluding the one that I have/know). If I have/know two of the cards voiced, then I know for sure the card that the player has. When I know for sure the card that the player showed, I can delete that column from my probability tables, update the utilities value to 0 and add that card to the cards found.

To update the values in the probability tables, these values are only updated if the previous value is different from 0 and less that the new probability values. The reason behind this is that if the previous value is 0, then we know that the player does not have that card, thus, we do not want to update it as we already have concrete information about it. If the previous value is bigger than the new probability, we also do not want to update it. For instance, if the previous probability is 0.5 and we want to update to 0.33 then it would not be beneficial for us because the previous value has a higher probability of a player having one card, thus, has more accurate information.

5.4.3.2. Player shows no card

When a player shows no card to another player, we know that player does not have one of the three cards voiced, but we can learn more information than this. We can check all the suspicions in which that player gave a card before and make inference of unknown knowledge. There are two cases: when two cards of the previous suspicion (i.e., suspicion the player gave a card) match two cards of the new suspicion; and when one card of the previous suspicion matches one card of the new suspicion. If there are two matches, then we know for sure the card that was showed in the previous suspicion. If there is only one match, there is 1/2 chance of the player having one of the cards voiced in the previous suspicion. However, if there is one match and we have one of the other two cards from the previous suspicion (the cards that did not match), we know for sure the player has the other card, which allows for further knowledge gain.

5.4.3.3. Update Utilities

At the end of each suspicion voiced, each player updates his utilities. Utilities can be update in three ways: if there is only one column left in the probability tables, if all values in a column are 0 and when the values in the probability tables are updated.

If there is only one column left, then the player knows this is the crime card, therefore, the utility value is updated to 1 and this card is stored as the crime card. If all values in a column are 0, then the player knows this is the crime card, because none of the other players has this card, therefore, the utility value is updated to 1 and this card is stored as the crime card. If none of these conditions are satisfied, then the player has not yet found the crime card and checks if there are any updates on the probability tables. The utility values are update by 1 minus the maximum value in each corresponding column in the probability table. The reason behind this is that the maximum value in each column represents the inference with higher knowledge. Furthermore, the probability tables represent the probability of each player having one card, and the utility values represent the probability of a card being the crime card, thus, they are complementary variables.

	M. White	C. Mustard	M. Peacock	M. Scarlett
player1			0	0
player2			0	0
player3			0.5	0
Player5				0
player6				0

Table 3 – Probability table of player that won using a Dynamic approach. M. Scarlett card is one of the crime cards.

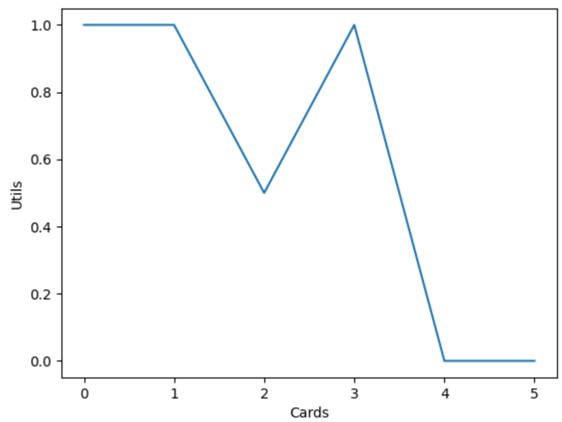

Figure 3 – Utilities graph of player that won using a Dynamic approach.

5.4.4. Naïve Approach

5.4.4.1. Update Utilities

Using a Naïve approach, a player only updates his utilities if there is only one column left in the probability tables as it means he has found all remaining cards in the game. Therefore, if there is only one column left, the utility value is updated to 1 and the card is stored as the crime card. However, if the player has not yet found the crime cards and no other player has cards to show when he voices a suspicion, he would be in an infinity loop as he would voice the same suspicion over and over. The reason behind this is that when using a naïve strategy, a player only makes inferences when a card is shown and has no knowledge when a card is not shown. To solve this problem, when no players show a card, the player must voice a different suspicion if he has not found the crime cards.

	M. White
player1	
player2	
player3	
Player5	
player6	

Table 4 – Probability table of player that won using a Naïve approach.

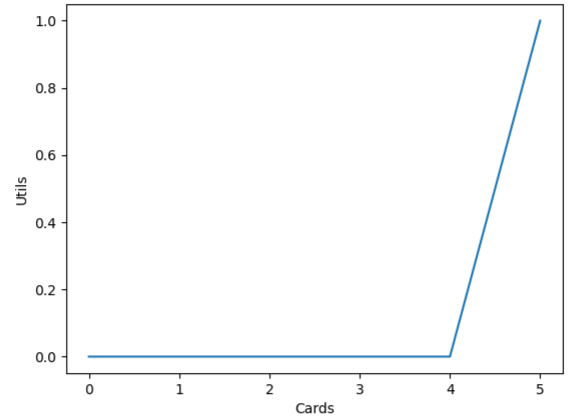

Figure 4 – Utilities graph of player that won using a Dynamic approach.

5.4.5. Accusation

At the end of each suspicion, the player that voiced the suspicion can decide to place an accusation or not. This decision is made when he has found all crime cards and he only finds this information when he updates his utilities. When any crime card is found, the suspicion voiced should include that card since this way he has a higher chance on gaining new information about unknown evidence. Furthermore, the decision behind an accusation will also vary depending on the personality of the player.

5.4.6. Personalities

There are two personalities: Bold and Cautious. A bold agent can place an accusation when has 50% or higher chance of that card being the crime card, whereas the cautious agent only places an accusation when he is 100% sure. These personalities can occur when using a Dynamic approach and Naïve approach. Using a Dynamic approach, a bold agent will find a crime card when: $\frac{Number\ of\ 0's\ in\ column}{nº\ of\ rows} \geq 50\%$ and a cautious agent will find a crime card when: $\frac{Number\ of\ 0's\ in\ column}{nº\ of\ rows} = 100\%$.

Using a Naïve approach, a bold agent will find a crime card when the probability table has only two columns left and so he should pick one of them randomly and a cautious agent will find a crime card when the probability table only has one column left.

	Library	Ballroom
Player2		0
Player3	0	0
Player4	0.5	0.5
Player5	0	0
player6		

Table 5 – Probability table of a bold player that lost using a Dynamic approach. In this example, the player guessed *Ballroom* as he was 60% sure but the crime card was actually *Library*.

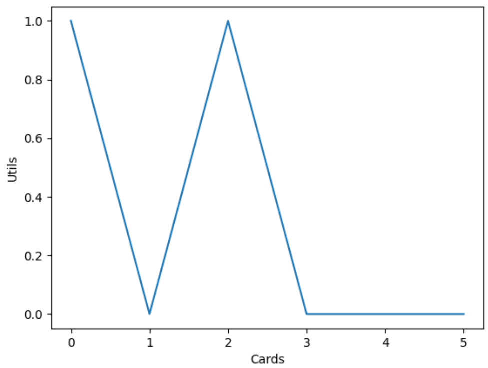

Figure 5 – Utilities graph of a bold player that lost using a Naïve approach.

6. EVALUATION

To analyze how the behavior of the agents changes according to the different metrics, we executed 1600 simulations.

6.1. Strategies

6.1.2. Results

We executed 100 samples for each combination of number of players using one strategy (e.g., we executed 100 games with 2 players using a Naïve approach and 100 games with 2 players using a Dynamic approach). We gathered 1000 samples, by testing with 2 to 6 players and using the two strategies. For each sample we stored the number of iterations per game as it represents the rounds it took for a player to place an accusation and either win or lose. To gather credible results from both strategies, we decided to execute the simulations using only cautious players. After, we averaged the number of iterations per 100 samples, calculated the corresponding standard deviations and gathered the following results:

	2Players	3players	4players	5players	6players
Naïve	19.39	36.59	47.77	57.95	87.34
Dynamic	8.39	13.12	14.56	16.99	21.22
Standard Deviations					
Naïve	1.601104	1.792774	1.884841	1.794351	2.239318
Dynamic	3.513021	5.168436	5.399813	6.084415	8.523977

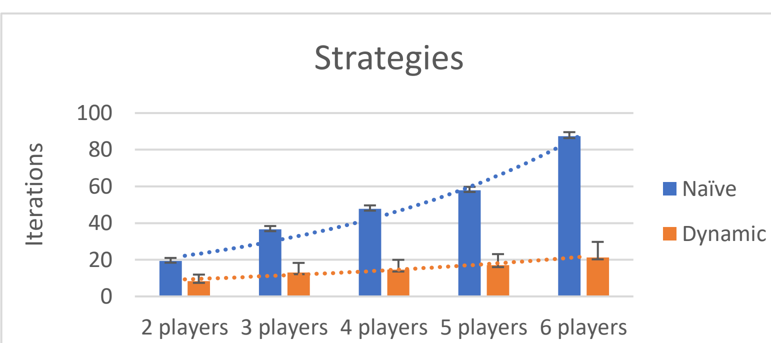

Table and Figure 6 – Average of iterations per 100 samples using each strategy.

6.1.3. Analysis

As shown in the graph, the Dynamic approach performed significantly better than the Naïve approach. This was as expected, because the Naïve approach does not consider the knowledge exchange due to communication nor does it consider conditional probabilities as a result.

The standard deviations of the Dynamic approach are slightly higher than the Naïve approach, because the number of iterations per game using a Dynamic approach can differ significantly. The reason behind this is that the cards are distributed randomly for each game, thus, a player can place an accusation in the first iteration as well as only in the twentieth, it all depends on what suspicion was placed and which cards the remaining players have. Therefore, we decided to run simulations with a large number of samples to acquired more accurate results.

Furthermore, as also shown in the graph, the number of iterations increases almost exponentially when the number of players increases, which is clearly shown in the Naïve approach. The reason behind this is that agents voice suspicions sequentially, thus, as the number of player increases, more iterations must be made so that a player can see a card (e.g., in a 2 player game, player2 will see a second card in the fourth iteration, and in a 6 player game, player2 will see a second card in the eight iteration).

6.2. Personalities

6.1.2. Results

We executed 100 samples for each combination of number of players using different personalities and using different strategies. We gathered 600 samples, by testing with 2, 4 and 6 players, equally dividing the players into 50% bold agents and 50% cautious agents and using the two strategies. We decided to only execute even number of players so that players could be distributed equally into bold and cautious agents and have equal chance of winning/losing. For each sample we stored the outcome of the game for the specific personality of the player that won/lost (e.g., bold player won, so we stored in a column named *bold* the string "won"). After, we decided to take two approaches: 1) count the number of "wons" per sample not considering the number of "losts"; 2) count the number of "wons" per sample but also considering the number of "losts".

6.1.2.1. First Approach

For the first approach, we counted the number of "wons" and divided by the number of samples, for each number of players and each strategy.

		Bold	Cautious
2 players	Naïve	0.32	0.1
	Dynamic	0.59	0.41
4 players	Naïve	0.31	0.02
	Dynamic	0.49	0.35
6 players	Naïve	0.28	0.02
	Dynamic	0.26	0.31

Table 7 – Contains number of "wons" per sample.

To properly analyze these results, first we calculate a F-test to understand if the population variances could be considered equal as these results are from different populations (i.e., different games with different number of players).

	Cautious	Bold
Mean	0.201667	0.375
Variance	0.030697	0.01779
Observations	6	6
df	5	5
F	1.725501	
P(F<=f) one-tail	0.28197	
F Critical one-tail	5.050329	

Table 8 – F-Test Two-Sample for Variances.

Having the null hypothesis being "the variances are considered equal", we can conclude that the null hypothesis is not refuted because the F value is less than the F critical value, thus, the population variances are considered equal. Knowing this information, we could proceed to calculate the T-test assuming equal variances.

First, we had to check if there is indeed a significant difference between the two variables so that we could compare them. We calculated a T-test with 0 as the hypothesized mean difference and $cautious = bold$ as the null hypothesis.

	Cautious	Bold
Mean	0.201667	0.375
Variance	0.030697	0.01779
Observations	6	6
Pooled Variance	0.024243	
Hypothesized Mean Difference	0	
df	10	
t Stat	-1.92818	
P(T<=t) one-tail	0.041342	
t Critical one-tail	1.812461	
P(T<=t) two-tail	0.082684	
t Critical two-tail	2.228139	

Table 9 – T-Test Two-Sample Assuming Equal Variances with 0 hypothesized mean difference.

To analyze this T-test, we had to check the t Critical one-tail value because this is the most appropriate when we want to determine if two groups are considered equal or not. As shown in Table 9, t Stat value is less than negative t Critical one-tail value, thus, the null hypothesis is rejected and there is indeed a significant difference between the two variables. Since we want to know if one variable is better than the other, we calculated a T-test with 1 as the hypothesized mean difference and $cautious > bold$ as the null hypothesis.

	Cautious	Bold
Mean	0.201667	0.375
Variance	0.030697	0.01779
Observations	6	6
Pooled Variance	0.024243	
Hypothesized Mean Difference	1	
df	10	
t Stat	-13.0523	
P(T<=t) one-tail	6.6E-08	
t Critical one-tail	1.812461	
P(T<=t) two-tail	1.32E-07	
t Critical two-tail	2.228139	

Table 10 – T-Test Two-Sample Assuming Equal Variances with 1 hypothesized mean difference.

To analyze this T-test, we had to check the t Critical two-tail value because this is the most appropriate when we want to determine if one group if greater than, or less than, the other. As shown in Table 10, t Stat value is less than negative t Critical two-tail value, thus, the null hypothesis is rejected and so we can assume that the bold player performed better than the cautious player.

6.1.2.1. Second Approach

For the second approach, we considered both the number of "wons" and the number of "losts". For this we used the following equation:

$$\frac{number\ of\ \text{"wons"} \times number\ of\ samples}{(number\ of\ \text{"wons"} + number\ of\ \text{"losts"}) \times number\ of\ samples}$$

		Bold	Cautious
2 players	Naïve	0.694736842	1
	Dynamic	0.59	0.41
4 players	Naïve	0.001616	1
	Dynamic	0.90303	1
6 players	Naïve	0.646465	1
	Dynamic	0.745562	1

Table 11 – Considers both the number of "wons" and the number of "losts" per sample.

To properly analyze these results, first we calculate again a F-test.

	Bold	Cautious
Mean	0.59690164	0.901666667
Variance	0.096451071	0.058016667
Observations	6	6
df	5	5
F	1.662471777	
P(F<=f) one-tail	0.295273138	
F Critical one-tail	5.050329058	

Table 12 – F-Test Two-Sample for Variances.

We did the same procedure as the first approach and concluded that null hypothesis is not refuted, thus, the population variances are considered equal. Knowing this information, we proceeded to calculate the T-test assuming equal variances. Again, we had to check if there is indeed a significant difference between the two variables and so we tested with 0 as the hypothesized mean difference and $cautious = bold$ as the null hypothesis.

	Bold	Cautious
Mean	0.59690164	0.901667
Variance	0.096451071	0.058017
Observations	6	6
Pooled Variance	0.077233869	
Hypothesized Mean Difference	0	
df	10	
t Stat	-1.899423732	
P(T<=t) one-tail	0.043352407	
t Critical one-tail	1.812461123	
P(T<=t) two-tail	0.086704814	
t Critical two-tail	2.228138852	

Table 13 – T-Test Two-Sample Assuming Equal Variances with 0 hypothesized mean difference.

Following the same procedure as the first approach, we can conclude that there is indeed a significant difference between the two variables because t Stat value is slightly less than negative t Critical one-tail value.

To check if one variable is better than the other, we tested with 1 as the hypothesized mean difference and $bold > cautious$ as the null hypothesis.

	Bold	Cautious
Mean	0.59690164	0.901667
Variance	0.096451071	0.058017
Observations	6	6
Pooled Variance	0.077233869	
Hypothesized Mean Difference	1	
df	10	
t Stat	-8.131844015	
P(T<=t) one-tail	5.10063E-06	
t Critical one-tail	1.812461123	
P(T<=t) two-tail	1.02013E-05	
t Critical two-tail	2.228138852	

Table 14 – T-Test Two-Sample Assuming Equal Variances with 1 hypothesized mean difference.

Following the same procedure as the first approach, we can conclude that the null hypothesis is rejected because t Stat value is less than negative t Critical two-tail value so we can assume that the cautious player performed better than the bold player.

7. Conclusion

From the results obtained, we can conclude that the Knowledge game *Cluedo* can be successfully modelled as a multi-agent system. The main goal with our system proposal was to find a way that would minimize the amount of movement but maximize the ability of the agents to reach their targets and this was accomplished with the Dynamic Epistemic Logic approach we implemented. This strategy can determine optimal movements in an environment in order to collect evidences from unknown targets and improve inference of unknown features, thus, can be an important asset for modern surveillance systems.

With the results and analysis obtained, it is possible to consider the following conclusions:

Do different strategies affect the efficiency in winning the game?

We analyzed two game strategies: Dynamic Epistemic Logic approach and naïve approach. The Dynamic approach outperformed significantly the Naïve approach, thus, we can conclude different strategies do indeed affect the efficiency in winning the game.

Do different agent personalities change the behavior of the agent and his ability to win the game?

We analyzed two personalities: Bold and Cautious. Different personalities do change the behavior of the agent because a bold agent places an accusation sooner in the game than a cautious agent. The behavior of an agent depends on the set of utilities which depend on the probability tables, thus, if one of these components is updated differently, the behavior of the agent will also change.

The approaches described in section 6.2. show that different agent personalities affect the agent's ability to win the game. The first approach shows that a bold agent performs better, and the second approach shows that a cautious agent performs better. However, the second approach is the one that considers the complete behavior of the bold agent (i.e., when he loses and wins), thus, this is the approach that should be used to analyze the agent's efficiency. Therefore, different agent personalities clearly change the behavior of an agent and his ability to win the game.

7.1. Further Research

As future work, it is possible to extend this implementation considering the following research lines:

- Create a Bayesian Network that can be used to visualize the behavior of each player and the dynamic of the game.
- Adapt the game implementation for a real-world problem, for instance, modern surveillance systems, treasure hunt, and more.

8. REFERENCES

[1] Wooldridge, M.: An *Introduction to MultiAgent Systems*. Newark: Wiley, 2003.

[2] Ditmarsch, H., Hoek, W., & Kooi, B.: *Dynamic Epistemic Logic*. In *Internet Encyclopedia of Philosophy*