

SME-Project-M

Project Report

at

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Fakultät Wirtschaftsinformatik und Angewandte Informatik (WIAI)

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**1 Abstract**

This report describes the work of the Meta-Team in the SME-Project-M in the Summer Semester 2018, supervised by Prof. Dierich Wolter and Prof. Ute Schmid. The aim of this project was to improve the BamBird 2017 agent by adding heuristic intelligence and to win the “Angry Birds AI Competition”.

It begins by describing the Angry Birds AI competition and provides a brief explanation of heuristics in artificial intelligence before proceeding to the BamBird 2018 no\_eclipse Agent.

**2 Introduction**

**2.1 Angry Birds**

Angry Birds is a popular physics-based simulation game [4]. In the game, the player controls a flock of multi-colored birds that are attempting to retrieve their eggs, which have been stolen by a group of hungry pigs [5]. In each stage of the gameplay, enemy pigs are sheltered by structures made of various materials such as wood, glass, ice and stone resembling children’s toy building blocks. The objective of the game is to eliminate all the pigs on the level. Using a slingshot, players launch a limited set of birds with the goal of either striking the enemy pigs directly or damaging their surrounding structures, causing the blocks to collapse and squash the pigs.

**2.2 Challenge for AI**

The challenge is to then build an AI player that can play new game levels as good as or better than the best human players. This is not an easy task although it would appear so when comparing to hard games like chess because of a number of reasons. Assuming all the parameters of the game world are known, we could simulate a number of actions and based on the outcome of the simulation, we could simulate a number of follow-up actions and so on until victory condition is reached. If we select the actions we simulate in an intelligent way, this could lead to a successful solution strategy. However, the main issue in physics-based simulation games is that the outcome of an action is only known once we simulate it, which in turns requires us to know all parameters necessary for simulation. This is very different from games such as Chess where the outcome of each action is known in advance. Accurately predicting or approximating the outcome of actions is one of the main challenge in the game. Combining this with the potentially infinite action space and the possible lack of complete information about all required parameters means that we are in for a big challenge. Humans are very good at predicting consequences of physical actions but this form of reasoning for AI agents remains a difficult task [4].

**3 Background**

**3.1 AI Birds and IJCAI**

The International Joint Conference on Artificial Intelligence is a gathering of artificial intelligence researchers and practitioners. The IJCAI 2017 conference was held in Melbourne, Australia and the IJCAI 2018 conference will be held in Stockholm, Sweden.

The Angry Birds AI Competition was help in conjunction with IJCAI 2017 conference and will be held again at the IJCAI 2018 conference. The goal of the competition is to develop an intelligent agent that can play the Angry Birds game as good as or better than human players.

In the AI Birds Competition, we play Angry Birds using the web version of the game. The competition server interfaces with the website using a Chrome browser extension which allows us to take screenshots of the live game and to execute different actions using simulated mouse operations. Participating agents run on a client computer and interact with the server using a fixed communication protocol. This allows agents to request screenshots and to submit actions and other commands which the server then executes on the live game. The participants obtain only the information of sequences of screenshots of the live game, therefore the agents have exactly the same information as a human player[4].

**3.2 Heuristic AI**

What is Heuristic AI?

Heuristic function is a function that generates alternatives at each branching step in a search algorithm to decide which branch to traverse next [2].

To understand what a heuristic search is and why it is useful, let us consider the example of 8-puzzle problem. The goal of the puzzle is to move the slides into empty spaces starting from the initial configuration to reach the goal configuration.

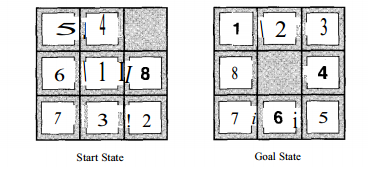


Fig 1 8-Puzzle Example

In most cases the goal state can be achieved in 20 steps, varying depending on the start state. The branching factor is about 3 (when the empty tile is in the middle, there are four possible moves; two when it’s in the corner, and three on the edge). With an exhaustive search to depth 20, this would give us 320 states [3].

This quickly becomes a problem if the game is much more complicated such as Angry Birds. Two factors immediately make it very difficult to even construct all states exhaustively during the game time. First is the unpredictable physics simulation. Because the operability of the physics of the game is unknown, producing all states exhaustive is restricted. We can create states and reproduce those states but only if the sequence of actions (shots taken for example) are kept same. The second factor is the limitation of time. To explore all possible states of all levels in the time given is not possible right now.

Thus we use heuristic functions to reduce this state count drastically. We keep track of states visited and use the information gained from those states to decide which action (or shot) to take next.

**4 The BamBird 2018 Agent no\_eclipse Meta**

**4.1 Creation of One Jar File**

Before we implemented the change, the BamBird agent was built with the Prolog function files external to the jar.

In this task the Prolog files into the Java/src folder so that when the jar file is created the Prolog files are within the jar file. And in the next step, the class PrologFilesCopier was created which is responsible for the copying of the Prolog files from the jar to an external directory so that these files can be accessed by the SWI-Prolog.

The PrologFilesCopier uses the class loader to request for a resource. The resource is read line by line and written to the external file again line by line.

**4.2 Meta**

Below we present that Meta algorithm.

**Algorithm 1** Meta

1: Load the ShotLearner database

2: **loop**

2: **if** GameState != Playing **then**

3: choose new Level using the new equation

4: **end if**

5: take a screenshot from the scene and analyse

6: generate plans

7: send the plans to the ShotLearner

8: select the shot returned by ShotLearner to execute

9: execute the selected shot

10: add shot to the shot-list of the current level

11: **if** GameState == WON or GameState == LOST **then**

12: add level to database

13: **end if**

14: add the shot to ShotLearnerDatabase

15: create a ShotResult object with the results of the shot

16: save the ShotResult to a log file

17: **end loop**

There are a few changes in the Meta algorithm from the BamBird 2017 agent. In the BamBird 2018 no\_eclipse agent that we present in this report, two new classes were added. The first is the ShotLearner class, described in more detail below, the second ShotResult, which is the POJO collecting results of the shot.

In the modified algorithm, the ShotLearner database is loaded before entering the game loop. The ShotLearner database is a list of ShotResult objects stored in a file. Then the game loop starts and if the game state is not playing, then we choose a level, using the new level equation as described in the section below. The algorithm then forwards the plans that it receives from Prolog to the ShotLearner class. The ShotLearner class returns one shot using heuristics and probabilities, this shot is then executed next. The results of the shot are stored as a ShotResult object into two different files, first is the ShotLearner database file and the other is the logs file. The logs file just collects information about the last run of the agent, as opposed the ShotLearner database which collects information about ShotResults over all runs of the agent.

**4.2 Level Selection**

There is one restriction when it comes to level selection – time, or in other words, the number of levels that can be played. In practice we found that on average the number of attempts are 1.5 times the number of levels in the competition. In the 2018 no\_eclipse Agent, we start playing the game from the first level and play each level once linearly. We call this the first round. After the first round, the agent creates a list of levels that it did not manage to clear them. This list of failed level is iterated once, and we call this the second round. In the third round the Agent uses the heuristic function to determine which level to play next.

Below, we present the heuristic function equation that we used to determine the potential gain.

Where,

P is Potential Gain

E is Estimated Maximal Points

B is Best Score

N is the number of times this level has been played.

In Round 2, levels are sorted by their potential gain and the level with the highest potential gain is selected to play next. Potential Gain is defined as the ratio of points that can still be gained for this level. This ratio is obtained by estimating the maximal points that can be achieved for this level. This estimation is achieved is by adding points for all pigs, plus some points for structure such as wood or ice, and assuming that we solve the level with just using one bird, the points of the remaining birds. Then we retrieve the best score we had for this level in Round 1 and then find the potential gain for this level by subtracting this best score from the estimated maximal points and dividing the result by the estimated maximal points.

Potential Gain is indirectly proportional to the number of levels played. This is significant because we want to agent to not repeat a level that has been found to be unsolvable in the previous attempts.

**4.3 Level Selection Evaluation**

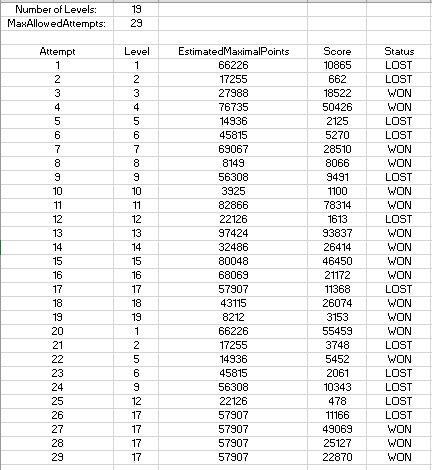


Fig 2 Level Selection Evaluation

In an evaluation run, we randomized the number of levels, the estimated maximal points and the score. The status of winning the level was dependent of scoring more than one fifth of the estimated maximal points. The maximum number of attempts are calculated as 1.5 times the number of levels.

We note that the Round 0 starts from Attempt 0 and finishes on attempt 19. Round 1 starts from attempt 20 and finishes on attempt 26. From attempt 27 to attempt 29 is the Round 2. Level 17 is won on attempt 27 but it is still the level with the highest potential gain and thus the agent tries to play the level for two more attempts.

**4.3 Shot Selection**

**4.3.1 Shot Learner**

Shot Learner is the class where the learning happens. After reading the database, the list of Shot Results is passed to the Shot Learner. This list is the background data for making probabilistic decisions. The main function of the Shot Learner class is to give feedback on whether a shot is good to execute or not. In the absence of data, the default answer is always true, meaning try out the shot.

For the following strategies the heuristics and probabilities are used: targetPig, domino, blackBird, collapseStructure, tnt, heavyObject and whiteBird. And for the following strategies the default value of true is returned: defrost, woodworm, bunker and roof. The default value of true was used for the last set of strategies because these strategies were encountered rarely and hence the number of examples were not sufficient enough to make a sound learning judgment.

Below, we present the algorithm of Shot Learner.

**Algorithm 2** Shot Leaner

1: Load the strategy from the Target argument

2: **if** strategy == strategyTypes **then**

3: get sub list of Shot Results with strategy as supplied in the argument

4: get sub list of Shot Results from (3) with the confidence as supplied in the argument

5: retrieve strategy specific counter

6: set result to true or false based on heuristics of the strategy specific counter

7: **end if**

The heuristic for Shot Learner is more semantic than Level Selection. There is no equation to make a decision on but rather an assumption that doing an action that results in some quantified value is better than doing some action that results in no value. We now proceed to discuss in more detail the strategy specific counter and heuristics for the first set strategy types.

* For the strategy type targetPig, the strategy specific counter is the number of pigs killed for the argument Target. Probability is calculated as the ratio of number of pigs killed to number of times this target has been executed. The strategy specific heuristic for targetPig is that if on average one pig is killed for this Target, then this Target is a good Target.
* For the strategy type domino, the strategy specific counter is the damage points. The probability is calculated as the ratio of total damage points to the number of times this target has been executed. The strategy specific heuristic for domino is that if the average of damage points is greater than 500 for this Target, then this Target is a good Target.
* For the strategy type blackBird, the strategy specific counter is the damage points. The probability is calculated as the ratio of total damage points to the number of times this target has been executed. The strategy specific heuristic for blackBird is that if the average of damage points is greater than 500 for this Target, then this Target is a good Target.
* For the strategy type collapseStructure, the strategy specific counter is the damage points. The probability is calculated as the ratio of total damage points to the number of times this target has been executed. The strategy specific heuristic for collapseStructure is that if the average of damage points is greater than 750 for this Target, then this Target is a good Target.
* For the strategy type tnt, the strategy specific counter is the damage points. The probability is calculated as the ratio of total damage points to the number of times this target has been executed. The strategy specific heuristic for tnt is that if the average of damage points is greater than 1000 for this Target, then this Target is a good Target.
* For the strategy type heavyObject, the strategy specific counter is the number of pigs killed. The probability is calculated as the ratio of total number of pigs killed to the number of times this target has been executed. The strategy specific heuristic for heavyObject is that if the average of number of pigs killed is greater than 1.5 for this Target, then this Target is a good Target.
* For the strategy type whiteBird, the strategy specific counter is the damage points. The probability is calculated as the ratio of total damage points to the number of times this target has been executed. The strategy specific heuristic for whiteBird is that if the average of damage points is greater than 250 for this Target, then this Target is a good Target.

**4.3.2 Shot Result**

After a shot has been executed, we retrieve the results of the shots and store them as an object of the ShotResult. The results of the shots include, the number of pigs killed and the damage points. This is then combined with the previous known knowledge of the shot, the bird type on the slingshot, the strategy to be used in the shot and the confidence of the shot. This class is a Plain Old Java Object (POJO).

**4.3.3 TargetAndShot**

This class collects two objects. First is the Target object that the ShotSelection had chosen to hit next and the Shot object that was generated for the corresponding Target object. Instead of returning just the Shot from the ShotSelection, we modified it to return a TargetAndShot object which consists of both the Target object and the Shot object.

**4.4 Shot Evaluation**

Below we present the evaluation of the Shot Selection for the first ten levels from the original levels of the game, compared with the agent at the start of the semester –

|  |  |  |
| --- | --- | --- |
| Original Levels | BamBird  (at the Start of the Semester) | BamBird  (no\_eclipse) |
| Level 1 | 29820 | 18700 |
| Level 2 | 50589 | 51130 |
| Level 3 | 30380 | 42530 |
| Level 4 | 20878 | 27880 |
| Level 5 | 0 | 64030 |
| Level 6 | 33013 | 17510 |
| Level 7 | 28348 | 27420 |
| Level 8 | 24316 | 37930 |
| Level 9 | 29768 | 41000 |
| Level 10 | 47458 | 38040 |
| Total | 294566 | 366170 |

Table 1 Shot Selection Comparison

We observe that our agent no\_eclipse performed 24.30% better than the agent at the start of the semester, scoring 71604 points more. We also observe that the no\_eclipse agent was able to clear Level 5. The maximum score for of Level 5 of other agents is, DATALAB 64460, EagleWing 64460 and IHSEC\_wAli 64740.

**5 Weka Machine Learning**

**5.1 Introduction**

Weka is a collection of machine learning algorithms for data mining tasks [6]. It includes methods for data mining problems such as regression, classification, clustering, association rule mining, and attribute selection [6]. Weka is used by applying a learning algorithm to a given dataset and analyzing its output. Another way of using Weka, which is relevant for our use in BamBird agent, is to generate predictions on new instances, and a third way is to apply different learning algorithms and compare their outputs and performances.

**5.2 Implementation**

For the use in BamBird, Weka is used to classify a new instance. The class to be learned is whether a shot is good or bad, this is called a relation in Weka. This relation is dependent on attributes, and the attributes for the BamBird agent are, strategy name, confidence class, damage points and pigs killed. Weka uses an ARFF[7] file. The ARFF file contains two sections, the header section and the data section. We give a brief description. Below we show the header of the ARFF file. The header contains the relation, a list of attributes and their data types.

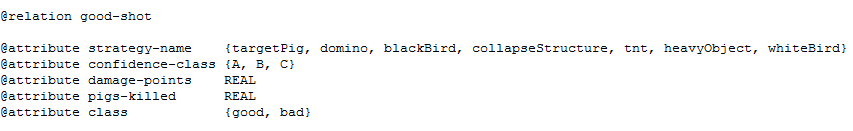


Fig 3 ARFF Header Section

The header section of the ARFF file is followed by the ARFF Data Section. It contains the data declaration line and the dataset. Below we show a snapshot of our training dataset. Default values from section 4.3.1 are used to mark a shot as good or bad. Confidence class is identified as follows: class A from 0.5 to 0.6, class B from 0.6 to 0.9 and class C from 0.9 to 1.0.



Fig 4 ARFF Data Section

In order to classify a new instance, a new ARFF file is created at runtime, called unknown.arff. The header of the unknown.arff is the same as the header described above, but the data section is different. Instead of having an entire dataset, only one data is provided, described below.

targetPig, A, ?, ?, ?

The ? is the dataset signifies unknown data. To classify this instance, we know that the strategy is targetPig and we know that the confidence-class is A, but damage-points, pigs-killed and shot class are unknown. We use the NaiveBayes algorithm as implemented by Weka to classify this new instance.

Following we present the updated Meta Algorithm for Weka and the ClassifyShot Algorithm, before proceeding to evaluation of the results.

**Algorithm 3** Meta-Updated

1: Load the ShotLearner database

2: **loop**

2: **if** GameState != Playing **then**

3: choose new Level using the new equation

4: **end if**

5: take a screenshot from the scene and analyse

6: generate plans

7: select the first Target from the plans and send it to WekaTester.

8: WekaTester classifyShot marks the Target good or bad.

9: **if** goodTarget **then**

10: execute the selected shot

11: **else**

12: remove the target from plan

13: go to 7.

14: **end if**

15: add shot to the shot-list of the current level

16: **if** GameState == WON or GameState == LOST **then**

17: add level to database

18: **end if**

19: add the shot to ShotLearnerDatabase

20: create a ShotResult object with the results of the shot

21: save the ShotResult to a log file

22: **end loop**

**Algorithm 4** WekaTester:ClassifyShot

1: create unknown.arff file.

2: write the header.

3: transform target into ARFF data instance

4: invoke NaiveBayes classifyInstance and save into prediction string

5: return prediction string.

6: **end**

Line 7 – 14 mark the difference in the updated Meta algorithm. A Target is selected from the generated list of plans and is sent to WekaTester, where this target is transformed into an instance and written to unknown.arff file.

There are two points of interest in Algorithm 4. The first is the transformation of Target object into ARFF data instance. This is trivial and is achieved by string manipulation and string writing onto the unknown.arff file. The second interest point is the invoking of classifyInstance of NaivesBayes algorithm. This is also trivial because the logic is abstracted behind a simple method call, shown below.

double predNB = nb.classifyInstance(newInst);[8]

where predNB is the predicted class, nb is the instance of NaiveBayes class algorithm and newInst is the new data instance that we wish to classify and predict the class of.

**5.3 BamBird Weka Evaluation**

Below we present the evaluation of the results achieved by Weka, and compare it to the results of BamBird agent at the start of the semester and the BamBird no\_eclipse agent.

|  |  |  |  |
| --- | --- | --- | --- |
| Original Levels | BamBird  (at the Start of the Semester) | BamBird  (no\_eclipse) | BamBird Weka |
| Level 1 | 29820 | 18700 | 18164 |
| Level 2 | 50589 | 51130 | 50153 |
| Level 3 | 30380 | 42530 | 42530 |
| Level 4 | 20878 | 27880 | 27729 |
| Level 5 | 0 | 64030 | 64088 |
| Level 6 | 33013 | 17510 | 17314 |
| Level 7 | 28348 | 27420 | 27091 |
| Level 8 | 24316 | 37930 | 37387 |
| Level 9 | 29768 | 41000 | 40655 |
| Level 10 | 47458 | 38040 | 37946 |
| Total | 294566 | 366170 | 363057 |

We observe that the overall score achieved with Weka is 3113 points less. In practice, we conclude that this is not a significant difference, hence the results of BamBird no\_eclipse and BamBird Weka are comparable. This is so because of the choice of the default values of strategy types to define a good shot, as described in section 4.3.1. Somehow these default values mark a sweet spot. If the default values are increased or decreased, BamBird Weka performance goes down in terms of total points. This is so because if the default values are increased, then more good shots are identified as bad shots, leading to shot scarcity which leads to BamBird shooting default shots. If the default values are decreased, then more bad shots are classified as good shots which leads executing shots that don’t generate any positive result.

**6 Conclusion**

**6.1 Future Improvements**

**6.1.1 Time Remaining Level Selection**

The new level selection formula does not use the amount of time remaining and the heuristics of how long a level takes to finish into account. It would be very effective to include such two factors into the equation because the 2018 Agent considers all levels to take equally long to solve, which is an assumption that works impractically in the gaming world. Some heuristics can be saved which could map level maximum points to time taken to finish the level or another strategy could be to use a mapping between the number of birds available in a level to the time taken to finish the level.

**6.2.2 Type of Level**

The 2018 Agent does not currently identify the level type. A definition of what constitutes a level type also has to be identified. It could be that some levels have something similar, for example level X has a structure and level Y also has. So the shot selected for Level X could also be used for level Y. There is a scope of employing machine learning and identifying and classifying similar levels.

**6.3 Conclusion**

In the duration of the Summer Semester 2018, we improved an intelligent agent by supplementing it with learning. Our approach has yielded success and we conclude that the BamBird 2018 no\_eclipse Agent performs better than the BamBird 2017 agent. Implementing learning algorithms from Weka do not influence the results.

**7 Literature**

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[6] Eibe Frank, Mark A. Hall, and Ian H. Witten (2016). The WEKA Workbench. Online Appendix for "Data Mining: Practical Machine Learning Tools and Techniques", Morgan Kaufmann, Fourth Edition, 2016.

[7] <https://www.cs.waikato.ac.nz/ml/weka/arff.html>

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