

Adaptive Game Difficulty

By

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Project report for IKT411 in Spring 2013

Faculty of Engineering and Science
University of Agder
Grimstad, 7th of June

Status: Final

Keywords: E-learning, gamification, unsupervised online learning, stochastic hill climbing, maximize fun

Abstract:

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3 Introduction

Today, there exists more commercial video and computer games (henceforth: games) than ever before, and the number of persons owning a smart-phone or personal computer is increasing. Many students and pupils neglect their studies in favor of watching television or playing games, maybe because they consider it more fun. We believe that through the use of E-learning and gamification, which enhances traditional learning methods with elements from games, it is possible to make any learning process more fun, resulting in more interested students and better grades.

As each student is unique, we believe that they also have different learning methods that work best for them, which is why we have chosen to look into adaptive games. In this project we research whether a game can be made, such that it adapts to each player on the fly.

3.1 Background

A lot of research has already been done on the area of E-learning, and there exists multiple definitions. We have chosen to use the following one, because it emphasizes the individual student, which goes hand in hand with individual adaption of application.

"We will call e-Learning all forms of electronic supported learning and teaching, which ... aim to effect the construction of knowledge with reference to individual experience, practive and knowledge of the learner..." [2].

Gamification is a concept that has been around for a long time, and has increased with popularity since 2010. [3] [4]. We present the two following definitions, as we think both of them show that gamification can be used well in conjunction with E-learning.

"The process of game-thinking and game mechanics to engage users and solve problems." [4].

"A process of enhancing a service with affordances for gameful experiences in order to support user's overall value creation." [5].

The latter definition is directed towards service marketing, but if one reads 'service' as 'learning process' and 'user's overall value creation' as 'learning outcomes', we believe that gamification is something that could be used together with both tradition learning methods and E-learning.

If one is to create a game that is meant for learning purposes, it is important to note that the game needs to be fun. [4]. If a game is not fun, it will not be able to educate either, because players lose interest in games the same way as students lose interest lectures, should they be boring. This is why it is important to figure out how it is possible to maximize the fun in any kind of game, thus keeping the interest of players. Since games appeal to a wide variety of players, the perceived level of fun may often vary among its players, due to personal preferences. In order to accomodate for such varying preferences, traditional games have often implemented several levels of difficulty the player may choose from, as well as providing the player with several settings or options for how they want the game to behave. When it comes to difficulty, other work has already been done on how to scale and adapt this to the level of player, in order to make even games, but in order to make a game fun, we believe that more than difficulty needs to adapt to individual preferences, thus more aspects of a game should be able to change on the fly. [6].

3.2 Problem Statement

Our project is to research whether it is possible to create a game, that uses an unsupervised online learning algorithm, which will adapt the game to the user's preferences based on limited user feedback.

3.3 Problem Solution

We have chosen to create a game using the tower defence genre, as this requires somewhat less work and graphics than many other genres, as well as having a lot of possible parameters that can be tweaked in order to adapt the contents of the game (henceforth: gameplay). The game uses a modified stochastic hill climbing algorithm together with some user feedback after each game, to adapt itself towards the individual player.

4 Stochastic hill climbing

A hill climbing algorithm is an iterative improvement algorithm, searching for a local maximum. It tries to maximize a function $f(X)$, where X could be a node, state, position or, in our case, a vector of parameters. It compares neighboring nodes to the one it is standing on, and checks if they are an improvement on $f(X)$. If one of the other nodes is improving the situation, then the algorithm moves to the new node, commonly the best node, and repeats the process. The process is repeated until no more improvements can be found, thus the algorithm has found a local maximum. [7]

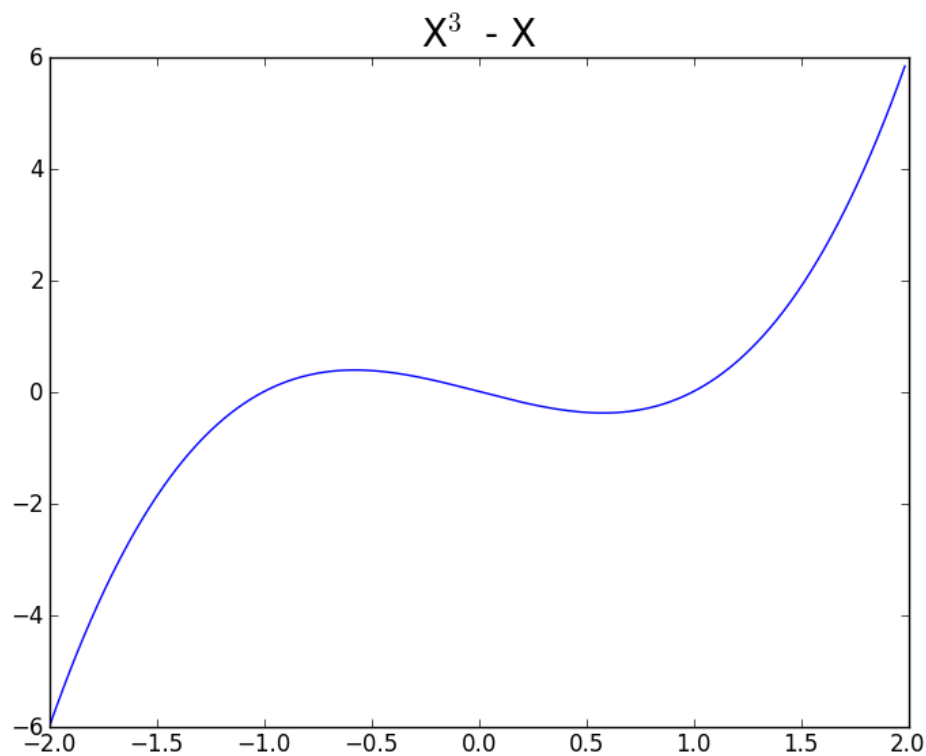


Figure 1: A function that has a local maximum

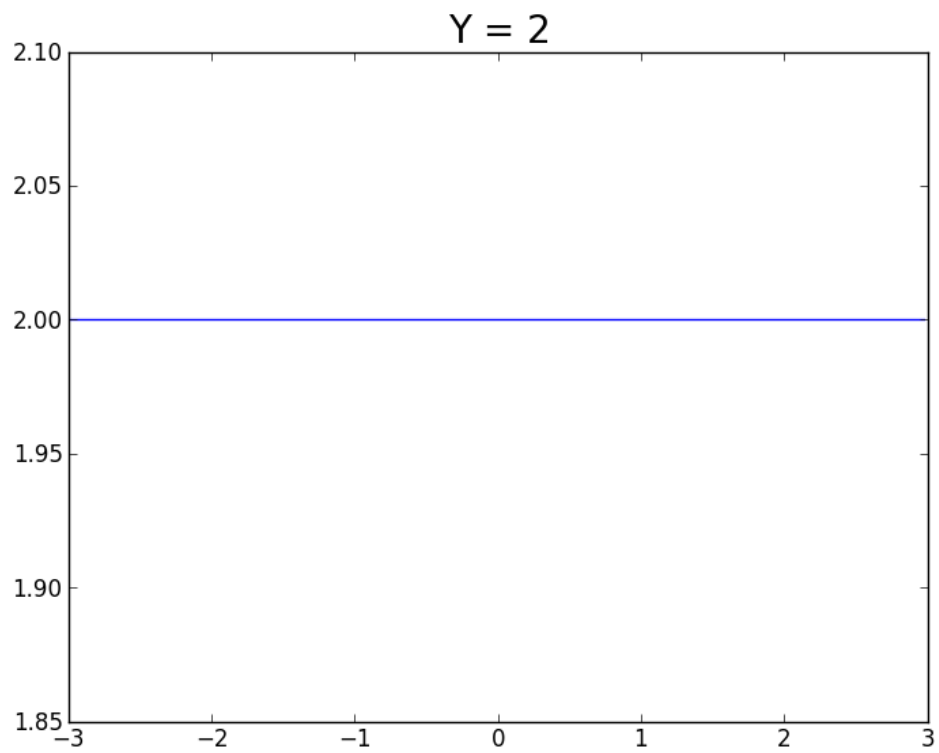


Figure 2: A function that is too flat to search on

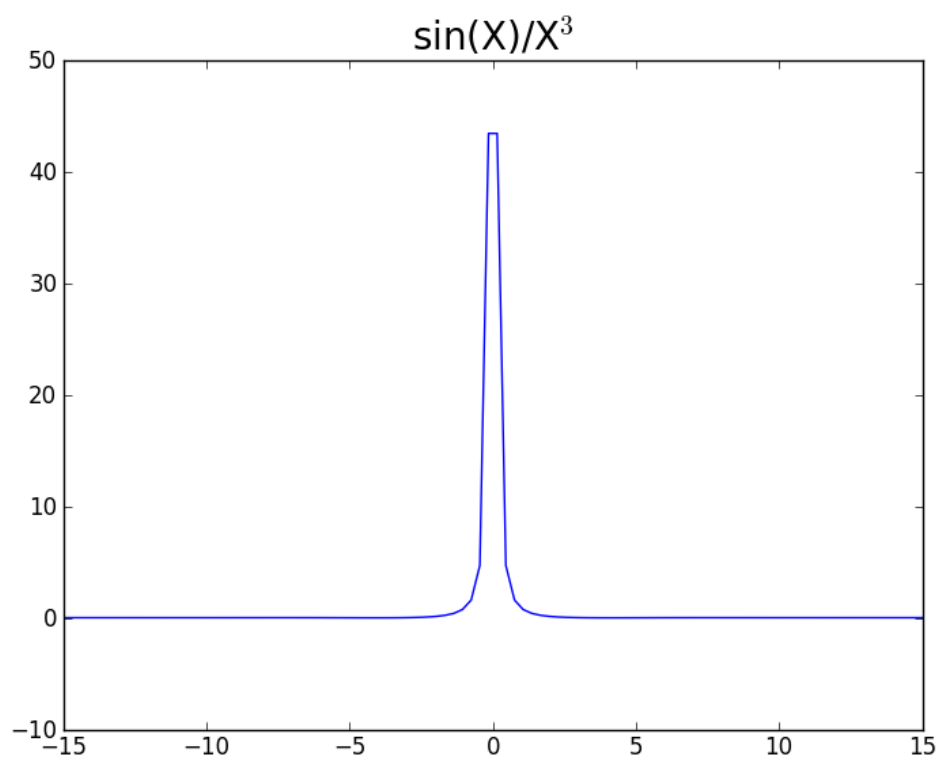


Figure 3: A function that is very steep

One issue with this algorithm, is that it can become stuck on a local maximum, which may not be the global maximum, as in *Figure 1*. One way to reduce the probability of this to happen, is to allow the algorithm to jump larger distances each jump, or to make sure that the landscape is convex. Another issue shown by *Figure 2* is that the search area may be flat, that is, each node is as good as all its neighbors. In this case, any jump will not bring any improvement. A third issue in *Figure 3* is that a node may be lying on a very steep ridge, that is, the 'area' of parameters that give a good node is very small, and can thus be hard to find. [7]

There are different variants of hill climbing algorithms, with different ways of deciding where and when to jump. The stochastic hill climbing algorithm, closely resembling simulated annealing, chooses a position at random, then evaluates whether it is an improvement, and if it is, jumps to the new position. If the new position is not an improvement, it will go back to the last one. With stochastic hill climbing, it may be wise to set a specific maximum jump distance, and let this decrease over time. This allows the algorithm to converge or settle on a position after some time. [7]

4.1 Stochastic hill climbing example

Here is an example for how to use stochastic hill climbing for how to find the maximum value of the function $f(X) = 2 - X^2$, which has a maximum value of 2. We initialize the maximum jump distance (in x-direction) to a value of 1.0, and let this decrease by 0.1 with each jump.

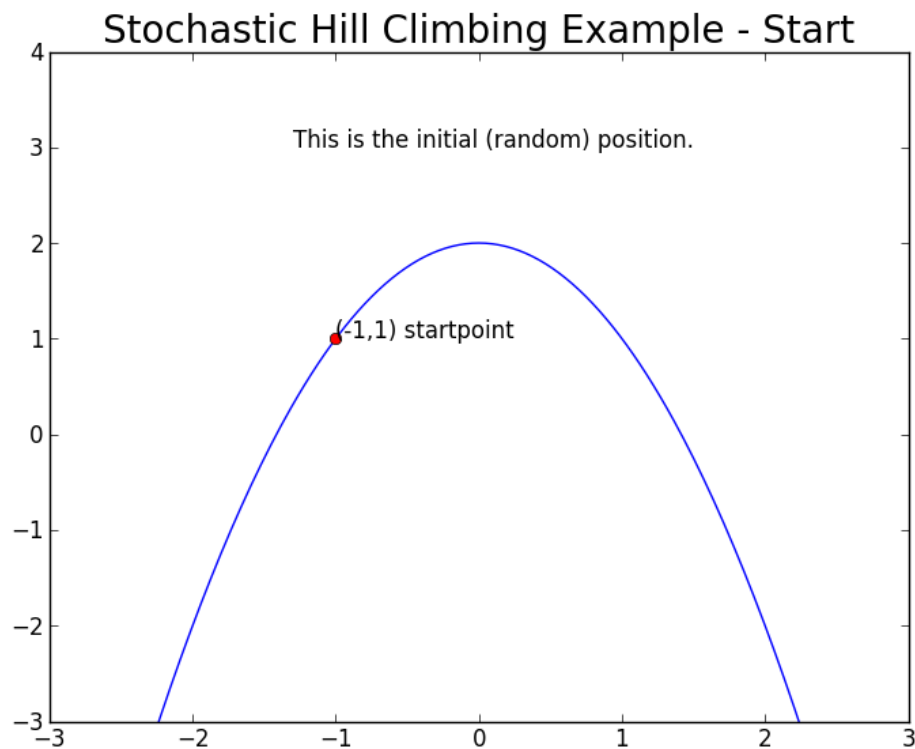


Figure 4: The startpoint for the search

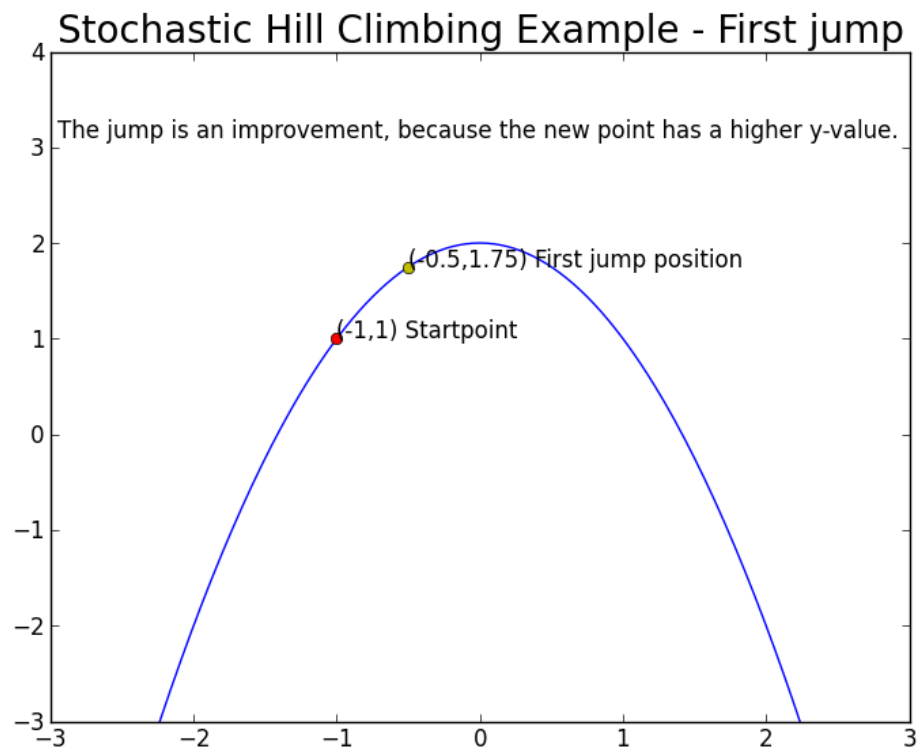


Figure 5: The first jump

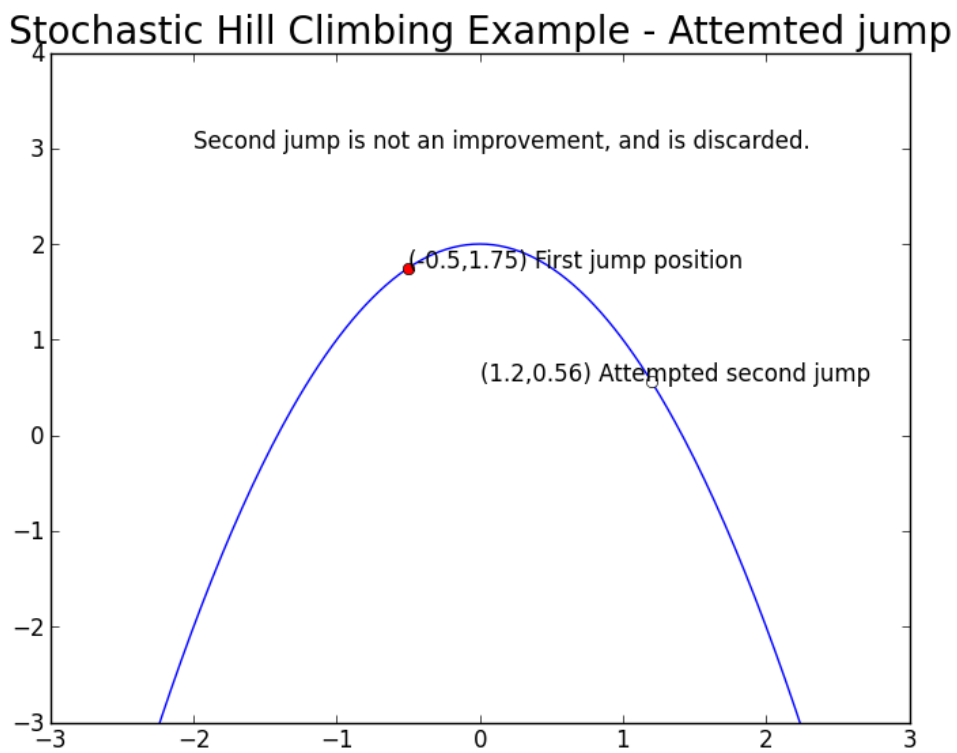


Figure 6: An attempted jump

Stochastic Hill Climbing Example - Global Maximum

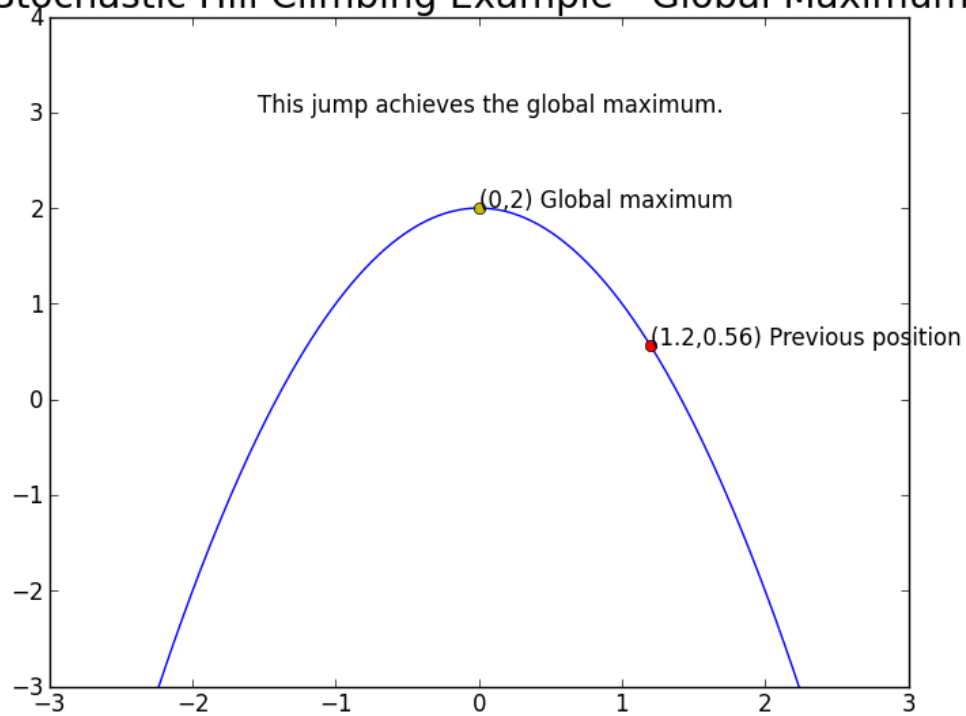


Figure 7: Achieving global maximum

Stochastic Hill Climbing Example - Further Jumps

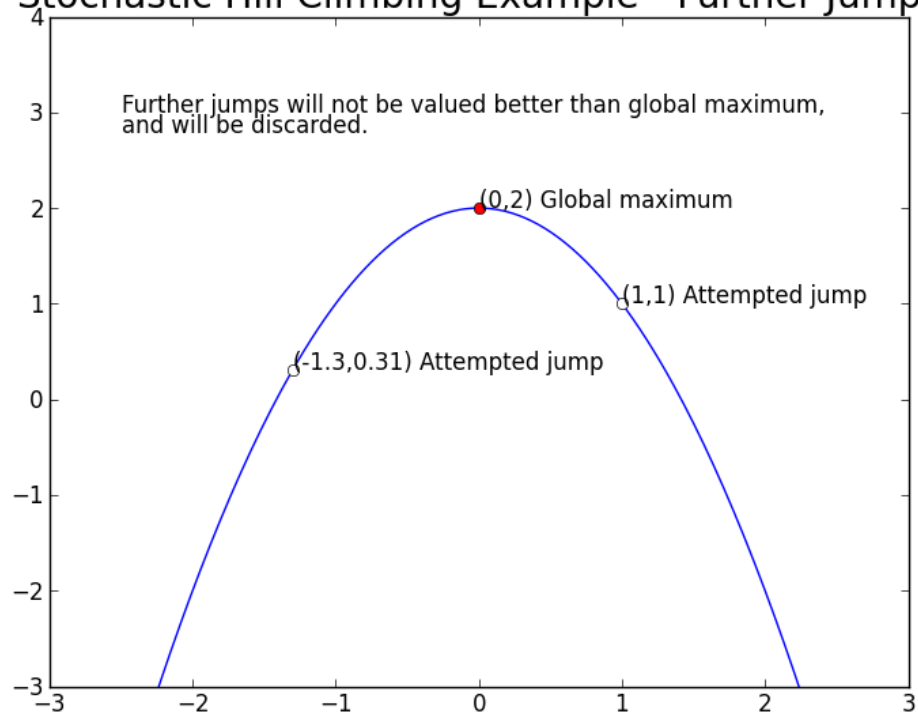


Figure 8: Further jumps are discarded

This is a short example of how stochastic hill climbing will eventually find the local, or global, maximum on a graph. This example is very short, compared to how many jumps it would normally take, but this is actually possible.

With a starting maximum jump distance of 1.0, decreasing by 0.1 with each jump, the algorithm will have converged after ten jumps, hopefully at an acceptable position. In a game setting, it may be wise to let the maximum jump distance never decrease to zero, because it can make the game feel more lively.

5 Game Description

This chapter gives some pictures and a short description of our game, as well as some general information about the game genre, namely tower defence.

6 Vår algoritme

As you can

If else when then so do stuff and dont sit there.

6.1 Genre

- Om TD generelt

6.2 Our game

Our game is very similar to classic tower defence games, in that the player has to stop different kinds of enemies from reaching the destination on their path, by using different kinds of towers. Our game differs from other tower defence games on the following:

- There are no scripted or static levels, since each game is a step closer towards the player's 'ideal game', that is, the game that is perceived as the most fun.
- Other than that the game learns after each level, the player has nothing that is carried over to the next game, such as tower access, special items or game progress in general. The player simply plays successive games until he or she quits.
- Modular towers and enemies. This is not necessarily new to the tower defence genre, as not all tower defence games may have pre-defined enemies and towers, but this is something that can be used in order to adapt the game towards personal preferences.
- (Guided) Randomly generated maps. Not necessarily new to the genre either, but is another useful technology that can be used to adapt the game to the player. Note that our game did not use this for game adaption, only to make the game seem less static.

7 Testing

Our testing is split into two parts. The first part contains two case tests of the algorithm, and the second part contains tests from our fellow students and friends.

7.1 Case tests

This is how our algorithm performed.

7.2 Fun tests

After we finished the game, it was mainly sent to friends at the university. They were told to test the game for as long as they wanted, and when they were finished, they sent us a logfile containing some information about their games. They were also asked to rate how fun they thought the game was in total.

As you can see in the table, the game was rated on average.gfdlgdfg. Which is not exceptionally fun, but not boring either.

8 Discussion

Gode ting er nettopp at det hele funket.

Dårlige ting er at vi ikke kunne lage et godt nok spill, som kanskje kan ha noe å si, ettersom vår research bit er kun én del av hva som gjør et spill gøy.

TD er kanskje ikke beste sjangeren.

9 Conclusion

Dette kan bli bra i fremtiden, om vi kan ta det videre. Vi vil nok bruke det i en annen spillsjanger, hvor vi ser mer forskjell.

JVs notes on future

- e-learning with individual adaption
- try it out on another game, in other genre
- spillet: Gjøre noe med diggers, earthquakes.
- Bedre grafikk i spillet, utvide content
- Guide søket til algoritmen

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IEEE, ACM, Springer

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