Machine learning neuroevolution for designing chip circuits/pathfinding

JONATHAN RINNARV, PONTUS BRINK

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Supervisor: Alezander Kozlov
Examiner: Örjan Ekeberg
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School of Computer Science and Communication

Abstract

Neural Networks have been applied in numeral broad categories of work. Such as classification, data processing, robotics, control e.t.c. This thesis compares using traditional methods of the routing process in chip circuit design to using a Neural Network trained with evolution.

Constructing and evaluating a chip design is a complicated thing, where a lot of variables have to be accounted for and therefore a simplified evaluation and design process is used in order to train the network and compare the results.

Sammanfattning

Skrivs när vi är nöjda med abstracten.

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Chapter 1

Introduction

A chip on a circuit board is a finely tuned and precise circuit map. Designing these chips depends on thousands of variables and would take a lot of computing power if you were to brute force every solution. The routing process of designing a chip is very precise, and must satisfy certain rules defined by chip foundries. The most important part of the routing process is to complete the required connections on the chip. After this, reducing wirelength and ensuring that the timing of each connection meets the conditions of the chip foundry rules. The routing process also has to take in parameters such as resistance, capacitance, wire width and spacing of each layer into account [5]. Modern circuits have reached such complexity that the use of computer tools are mandatory in design and evaluation of these circuits [1]. Finding the best path here isn't always the shortest possible one. In some situations, a path that is longer with less turns is favorable to the shortest possible one and sometimes a route may be required to take a longer path in order to satisfy some signal timing constraint. The environment has a large impact on which path is the most optimal one [13]. In critical sections of the circuit, some manufacturers even recommend manual routing [9].Therefore, traditional pathfinding algorithms that find the shortest path aren't guaranteed to give the best solution.

Using Neural Networks, a pathfinding algorithm that behaves and reacts differently according to the environment can be constructed. One could create a fitness function that generates a behavior required in one environment, which could generate a behaviour that is optimal for that situation. In order to do this, intensive knowledge about chip circuits is required, and the ability to score a design with a numerical value. With chip circuits being so complex, this is beyond the scope of this project and a simplified version of reality is used.

1.1 Problem statement

How can an artificial neural network be trained to solve the routing problem in circuit design? We will seek to answer this question by comparing the neural network to algorithms commonly used as a basis for industrial solutions. We consider the chip circuit to be a grid where two tiles are to be interconnected. There can also be tiles that the path can not be routed through. The intention is to evaluate the methods on the resulting path from a chip design point of view, using a fitness function designed for this.

1.2 Scope

General pathfinding functions such as A*star and maze search are covered in this paper. As well as a comparison between these algorithms and a Neural Network trained for pathfinding.

Constructing and evaluating a chip design is a complicated thing, where a lot of variables have to be accounted for and therefore a simplified evaluation and design process is used in order to train the network and compare the results. The simplified methods are described in detail in section 3.1.

1.3 Purpose

This report examines the differences between industry routing methods with the performance a trained Neural Network can produce. The purpose is to compare the more general, standard way of pathfinding in the routing process of chip circuit design to that of a trained Neural Network, taking into account variables such as speed and the resulting path.

Chapter 2

Background

2.1 Neural Networks

A neural network is a mathematical model of a brain and have can be described as a layer of states. The first layer is the input layer for the given problem. This layer feed its information forward to the next layer called hidden layer. The information progress through all hidden layers until it reaches the last layer, the output layer, which is the predicted solution for the given input. How the information flow through the network is not meant to be designed by an engineer, instead the network gets trained through rewarding it when it gets a prediction right and punishing it when it gets it wrong. Depending the amount of hidden layers a neural network can make more abstractions of the information and learn to analyze more complex tasks.

A popular method in training a network is supervised learning, that is when the network is fed a solution or a part of a solution and the input for that solution and update the network's internal state using the backpropagation algorithm. The algorithm calculates how far off the network's prediction was the expected value and back-propagates the error backwards through the network and adjust the weights between the layers to minimise the error [12][2].

Neural networks is not a new invention and have been around for a very long time [14]. Due to increase in computing capability of modern computers neural networks has been able to solve a wide range of complex tasks such as character recognition and stock market prediction [15].

2.2 Genetic Algorithms

Genetic algorithms are evolution inspired algorithms used to find an optimal solution to a problem. Often very expensive in form computing power but have been found to solve difficult problems like Database Query Optimization [3] and optimizing wind turbine farms [11].

The idea behind genetic algorithms is that you start with a simple creatures trying to solve the problem at hand. You let the best performing creatures reproduce and kill of the rest. You allow creatures to mutate and compete for survival. Given enough generations you hopefully have a creature able to solve the problem efficiently.

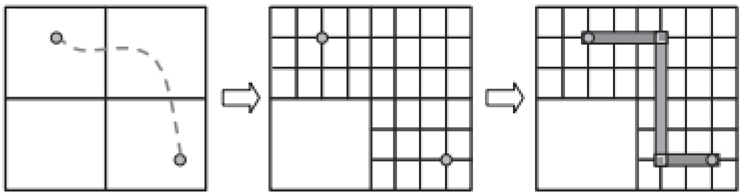
2.3 Neuroevolution of Augmented topologies

One of the main problems with genetic algorithms face is when a creature innovates and make a drastic change it will most likely perform worse than its parents did initially because it needs time to optimize and perfect its innovative niche. This often leads to the death of the creature and there by a potential solution is lost.

Year 2002 Kenneth O. Stanley and Risto Miikkulainen released a paper tackling this very issue, they call it Neuroevolution of Augmented topologies or NEAT for short [17]. They argued dividing the population of creatures into species and thereby letting creatures compete within their own niche will preserve innovation and will result in faster learning. This way they were able to create neural networks faster they other genetic algorithms [18]. They also developed a new way of creature crossover (mating) by tracking genes to their historical origin. Genes that two creatures share are always passed down to offspring and genes that differs are passed down from the fittest parent. This way children has lower chance of losing expertise which their parent obtained [19]. This led to NEAT to be able to start with a minimal neural network (only input and output) and not a random array of starting networks as other neuroevolution systems requires. This makes NEAT have a bias towards minimalistic solutions which is important to be able to keep the search space to a minimum to increase performance [20].

2.4 Routing process

Routing is an important step of the integrated chip design process. It generates the wiring that connect pins of the same signal while obeying the manufacturing design rules [5]. With the technology advancing, and the number of transistors on a single chip can reach into the billions, this challenges physical design and therefore the routing process. The routing process is split into global routing and detailed routing. In the global routing stage a routing region is constructed for each net on the chip and each net is given a tentative route through the set. The global routing part does not handle drawing how each wire connects, that is handled in the detailed routing process [8]. The global routing process essentially creates a grid with interconnected points that the detailed routing process then defines more clearly using channels and layers and also taking into account all the various parameters that affect the circuit such as interference (or crosstalk), density, heat and damage that can cause discharges [5]. The following pictures illustrates the global routing process (picture a and b) and the detailed routing process (picture c) with a simple example

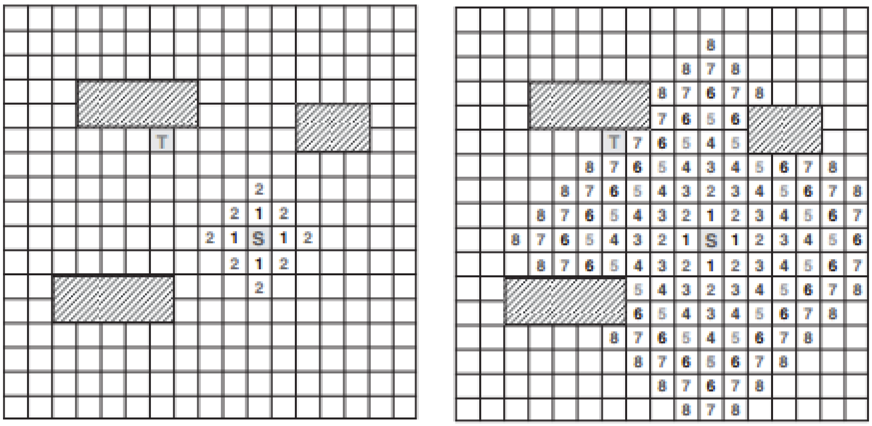


In picture A, regions that the net will use are defined. In picture B, the tentative route is given by the generated grid, the wire is allowed to be drawn through these nodes. In picture C, the detailed routing process has found a path through the grid.

Both the global and detailed routing process use general pathfinding algorithms so the following sections describe two popular algorithms for pathfinding used in both these processes.

2.5 Maze search

Maze search is a pathfinding algorithm that uses a BFS. It is suitable to use a Maze search when you have a unweighted graph with one source node that needs to go through a number of destinations or a number of source nodes that all have the same destination [6]. These types of problems appear in both the detailed and global routing processes, making maze search a useful algorithm for pathfinding [5]. This algorithm was invented in 1950 by E.F Moore, but later in 1961 C.Y. Lee discovered it independently and used it as a routing algorithm [4][10]. How maze search works is that expands outward from the starting node. It checks each neighbour node of the visited node until it finds its destination. Each time it checks a neighbour node, it increments a value on that node in order to find the shortest path to it from the starting node. For multiple destinations, the algorithm would continue from the starting node until all nodes has been reached. For multiple starting nodes, the algorithm would start from the destination instead and work the same way. The following pictures illustrates how a maze search algorithm works, where S is the starting node, T is the destination node and shaded areas are blocked and can not be routed through.



Maze search guarantees to find a path between the starting point and the destination given that such a path exist, and it also guarantees that the found path is a shortest path. It is however slow and memory consuming, its time complexity is O(mn) where m and n is the height and width of the grid.

2.6 A*Star

A*star is a heuristic pathfinding algorithm, meaning that it uses a evaluation function to determine which node to visit next. A*star is best fitted to use when you only have one starting node and one destination node. The function used is f(x) = g(x) + b(x) where g(x) is the cost of visiting the next node, and b(x) is the estimated cost from that node to the destination. [6]. An interesting note is that Maze search is a special example of A*star where b(x) = 0 for all x. Also, if b(x) has the never overestimates the cost from the current node to the destination, A*star would be optimal. If you only allow horizontal and vertical movements (Manhattan routing), b(x) could be set as the Manhattan distance to the destination, since it is the smallest distance from the current node to the destination b(x) would never overestimate the cost. A*star algorithms proposed in 1984 by and 1995 are used in modern routers. [5]. Since A*star use a heuristic function, its complexity depends on the used function. If one would choose that b(x) = 0 for all x, A*star would be the same as the maze search algorithm and share its complexity. In the worst case scenario, when the search space is unbounded, its complexity would be O(db) where d is the shortest path to the destination and b is the average number of childs from each visited node [16]. Like Maze search, A*star guarantees that if there exists a path from the starting node to the destination then A*star will find one. A*star does not however guarantee that it finds a shortest path, it depends on the quality of the used heuristic. A*star only guarantees that the found path is a shortest one if b(x) is less or equal to the actual cost, the smaller the b(x) however, the longer time A*star will take [7]. Below is a picture illustrating A*star with a manhattan heuristic. The red tile is the starting node and the blue tile is the destination. The colored nodes give the b(x) value ranking from yellow to blue depending on the estimated cost where yellow is the largest cost and blue is the lowest.

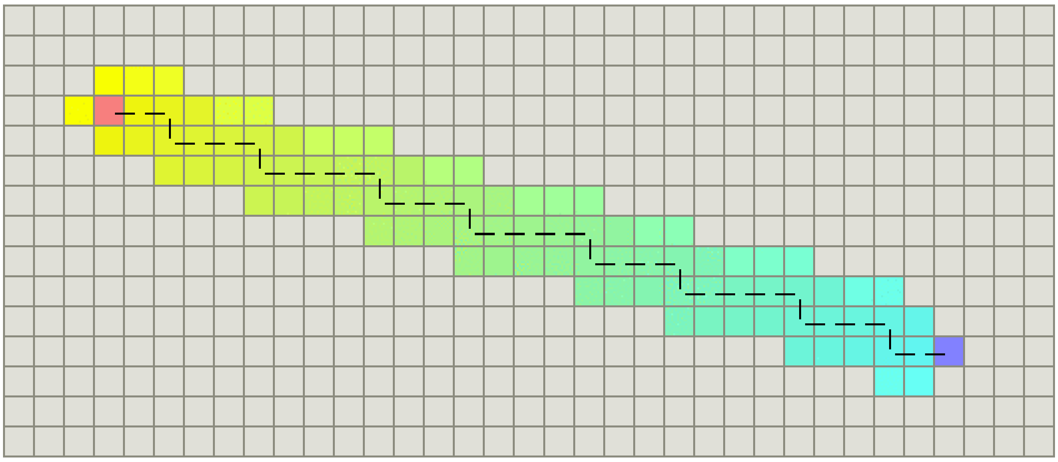


Figure 2.1: A*Star pathing example

Chapter 3

Method

This chapter describes how the Neural Network was constructed, how A*star and BFS was implemented and how the results were generated.

3.1 Environment

Because of time constraints in this course and the fact that circuits are extremely complex, restrictions have to be set to the routing environment. First we assume that chip circuits are only two dimensional and the parameters for evaluating a circuit are only wire length and amount of wire turns.

The simplified circuit are represented in the form of a two dimensional bit matrix where the value of 1 represent a unpathable tile and the value of 0 represent pathable tile. This matrix will change during the wiring process, laying down a wire will switch a tile from pathable to unpathable.

3.2 Neural network setup

The input layer starts with the matrix described in section (TODO: Environment). As well as the position of each wire and the corresponding destination (TODO: Formulera detta tydligare). For a circuit with size 10x10 with two wires to rout the amount of inputs would be 10x10+4x2=108. The output layer consists of four actions for each wire, move east, move north, move south and move west. For the example above the amount of outputs would be 4x2=8. The output from the network is an array of prefered moves. Each wire has four directions it can move. The neural network outputs an array with these moves and the highest rated move is chosen. If this move is illegal the next on the list is chosen in its place. If all moves are exhausted the evaluation of the network is done.

3.3 NEAT parameters

Mutation rate on weights is set to 0.8. A low mutation rate result in a stable network performing close to there parent. A high value results in a highly diverse network who can out perform its parent with high margin but risk losing what made parents successful.

Add new node rate is set to 0.2. A high rate can easily result in redundant nodes with no function. This rate was set low to strive after the minimal solution. This is important to keep the networks as small as possible to save time on evaluating them.

Add new connection rate is set to 0.5. A high rate can result in redundant connection between nodes but a low rate can result in new nodes never get used and experimented on.

The initial connection on a new network in set to empty with no connections. This is to save computing time and stay bias towards a minimal solution.

3.4 A*Star and BFS

The A*star and BFS algorithms were implemented using the pseudo code in the appendixes. When the input uses multiple start and end node, every permutation of the wire order is generated, each solution is generated and the one that creates the best fitness is chosen. In order for these algorithms to create the optimal solution, each shortest route must also be explored with each wire order. This is not something A*Star is able to do whilst remaining more efficient than BFS. Therefore, because of this and the time it would to take to test every solution on complicated inputs, only wire order permutation were implemented.

Chapter 4

Result

This chapter presents the result of the testing of the algorithms

4.1 Test 1

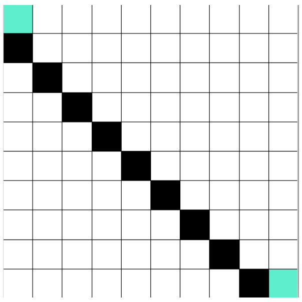


Figure 4.1: Base

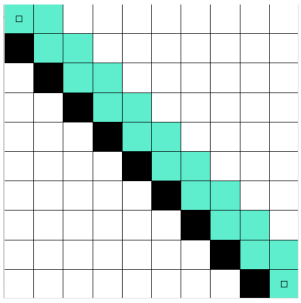


Figure 4.2: A*

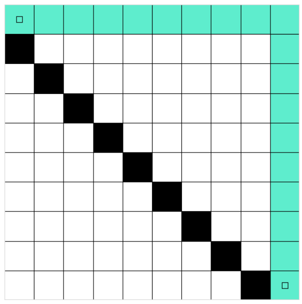


Figure 4.3: NEAT 0 hidden nodes

Figure 4.4: Test 1 - NEAT generated 0 hidden nodes

This is the first test we used to compare the algorithms. Both BFS and A*star resulted in the same path with a fitness of 43. NEAT achieved a fitness of 77. This is a 79% better fitness than A*star and BFS.

4.2 Test 2

This is the second test used to compare the algorithms. BFS, A*star and NEAT all gave different results, with A*star achieving a fitness of 142,

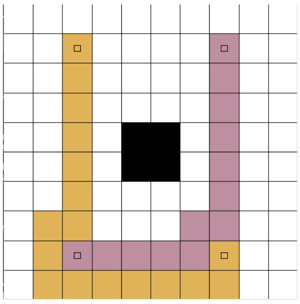


Figure 4.5: A*

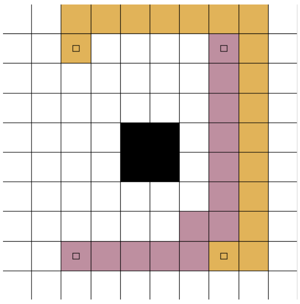


Figure 4.6: BFS

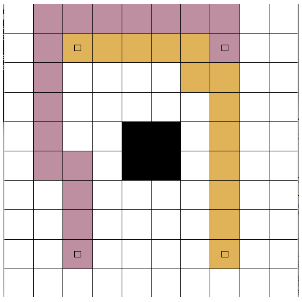


Figure 4.7: NEAT 0 hidden nodes

Figure 4.8: Test 2 - NEAT generated 0 hidden nodes

BFS a fitness of 154 and NEAT a fitness of 152. NEAT its best solution after only five generations, but it was run for 150 generations.

4.3 Test 3

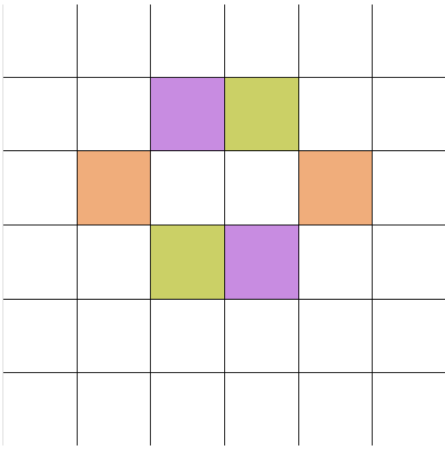


Figure 4.9: Base

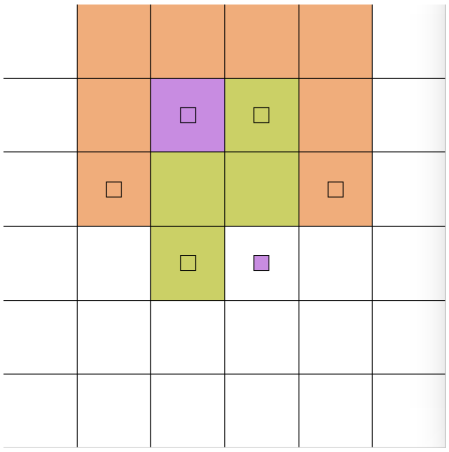


Figure 4.10: A*, BFS and NEAT 0 hidden nodes

Figure 4.11: Test 3 - NEAT generated 0 hidden nodes

The third test we used is impossible to complete all the wires. In this test, every algorithm constructed the same paths and was able to find one of the best solutions with a fitness of 176.

4.4 Test 4

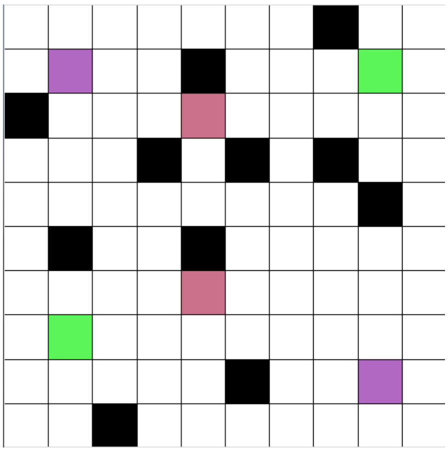


Figure 4.12: Base

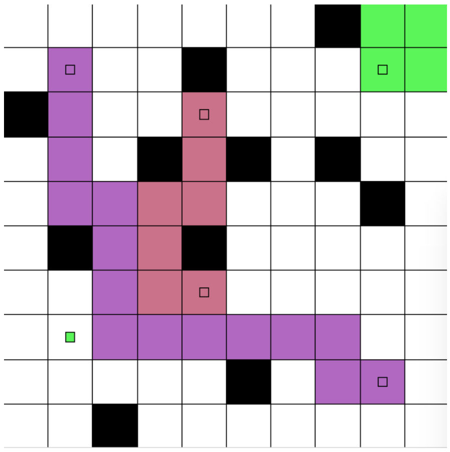


Figure 4.13: NEAT after 173 generation. 4 hidden nodes

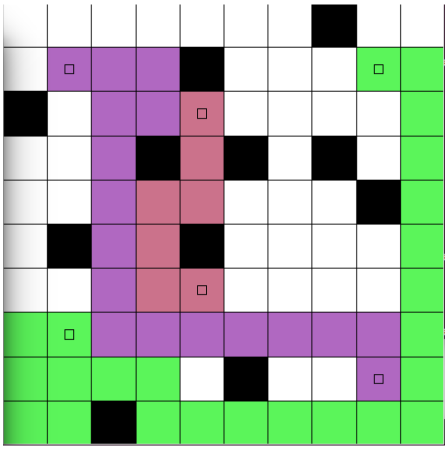


Figure 4.14: NEAT after 578 generations. 5 hidden nodes

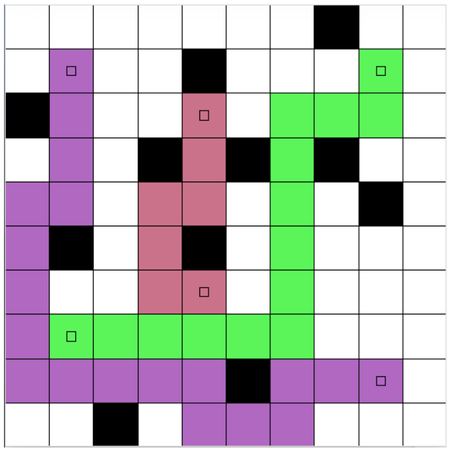


Figure 4.15: A*

Figure 4.16: Test 4 - NEAT generated 5 hidden nodes

NEAT after 173 generation acquired a fitness score of 148. NEAT after 578 generation acquired a fitness score of 185. A*Star scored a fitness of 204.

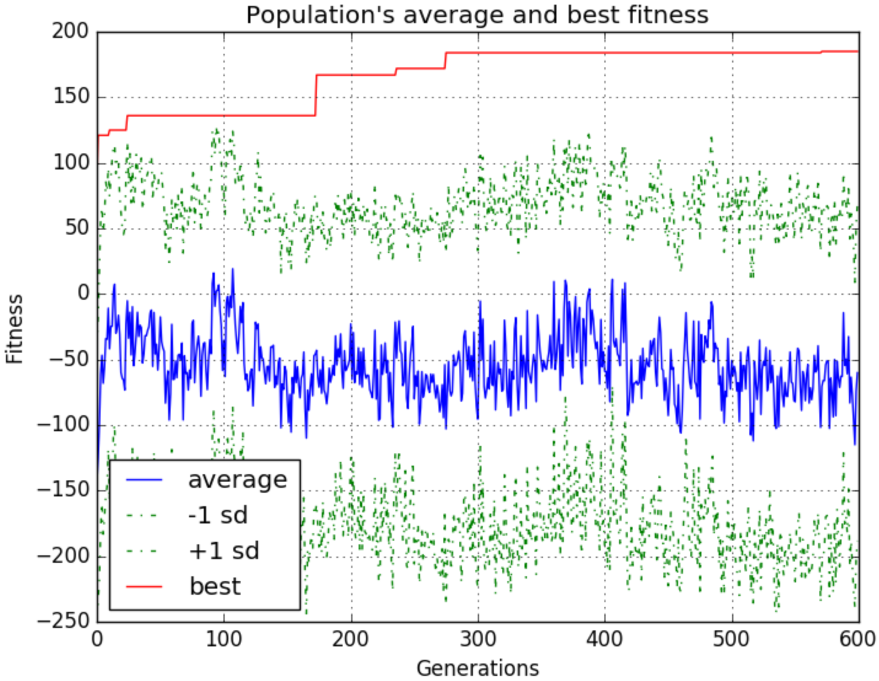


Figure 4.17: Test 4 - NEAT Fitness graph

The best fitness was found at generation 578. The best fit curve steadily increases early and begins to converge at 270 generations while the average does not increase during the session.

4.5 Test 5

This is a test with a grid of size 35x35 with five wires to path. NEAT had 1245 inputs and 20 output.

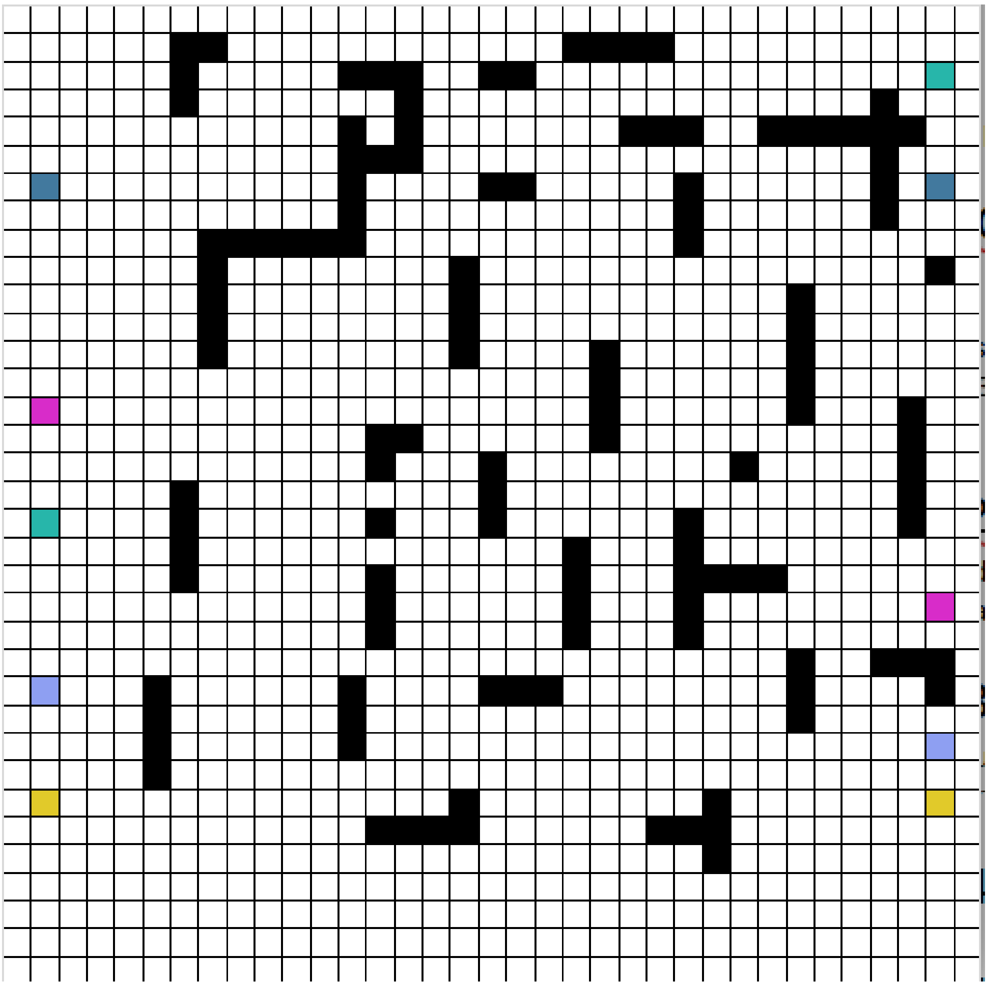


Figure 4.18: Test 5 - Base. Grid of size 35x35 with 5 wires

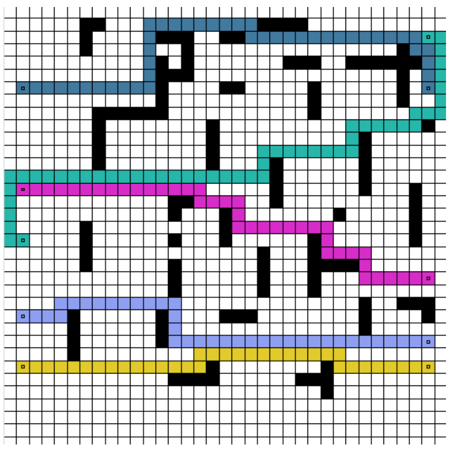


Figure 4.19: A*

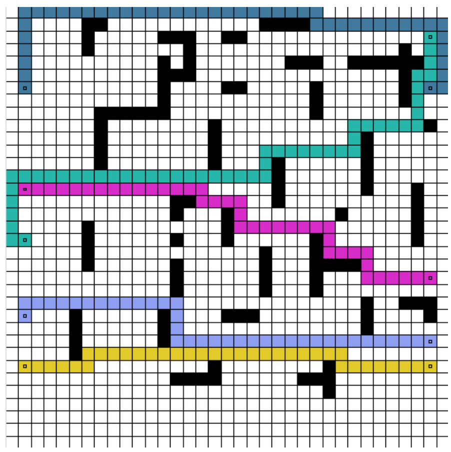


Figure 4.20: BFS

Figure 4.21: Test 5 - A* and BFS

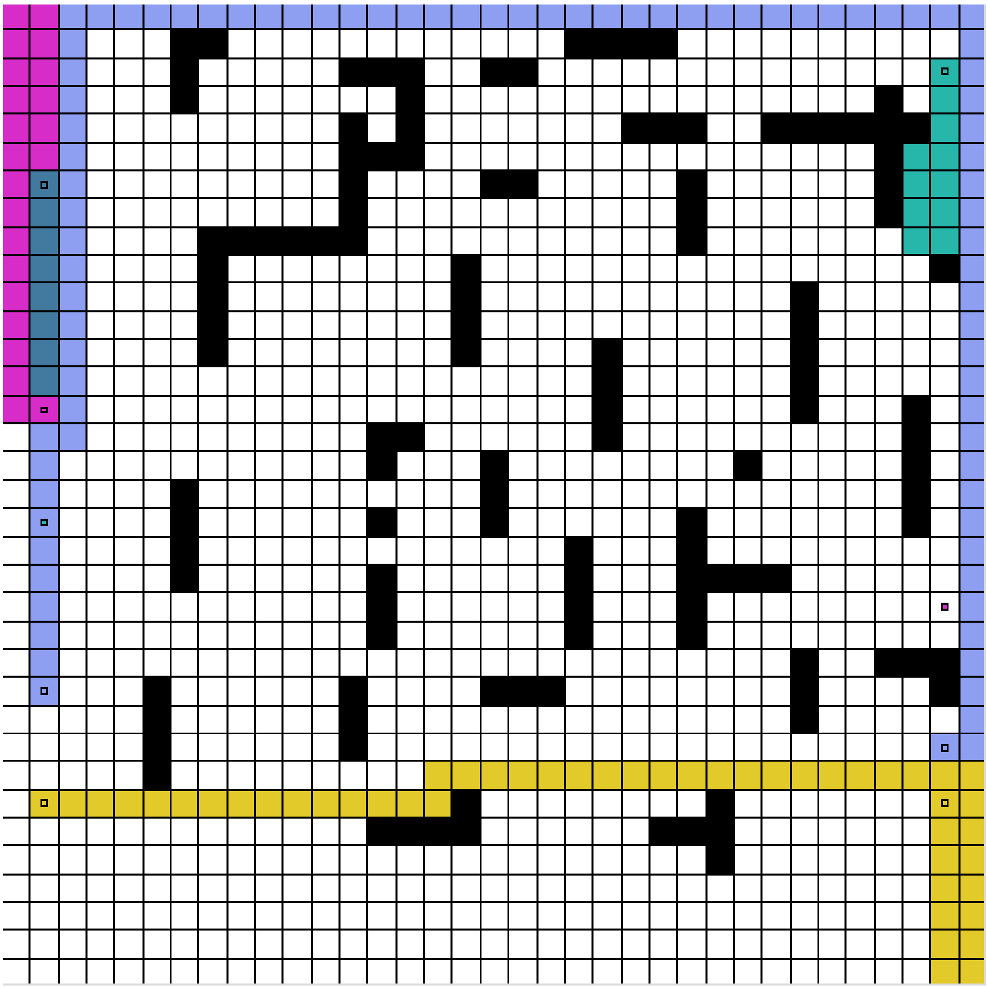


Figure 4.22: Test 5 - NEAT After 26 generations. 0 hidden nodes

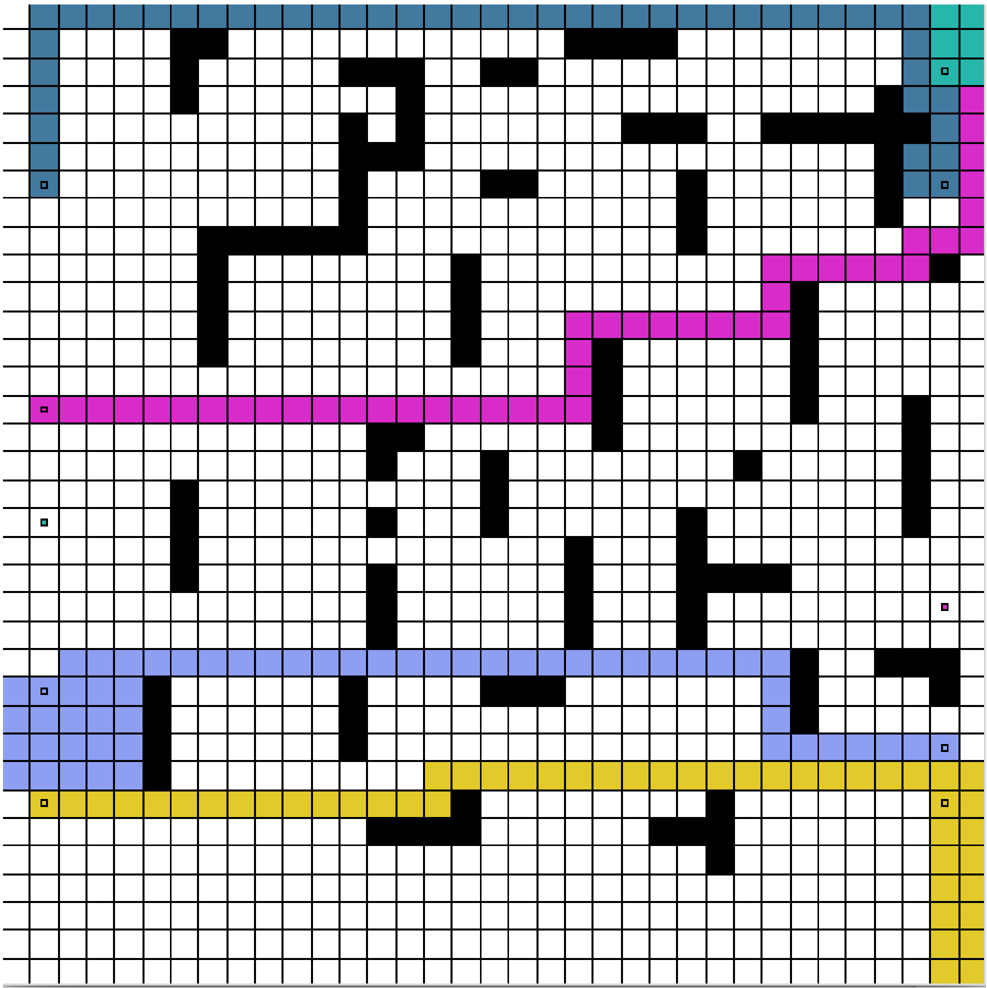


Figure 4.23: Test 5 - NEAT After 300 generations. 1 hidden nodes NEAT 300 generations Fitness: 8, NEAT 150 generations Fitness: -72, A*star fitness 296, BFS Fitness 296. A*star and BFS got a fitness 3700% higher than the best NEAT neural net could generate within its session.

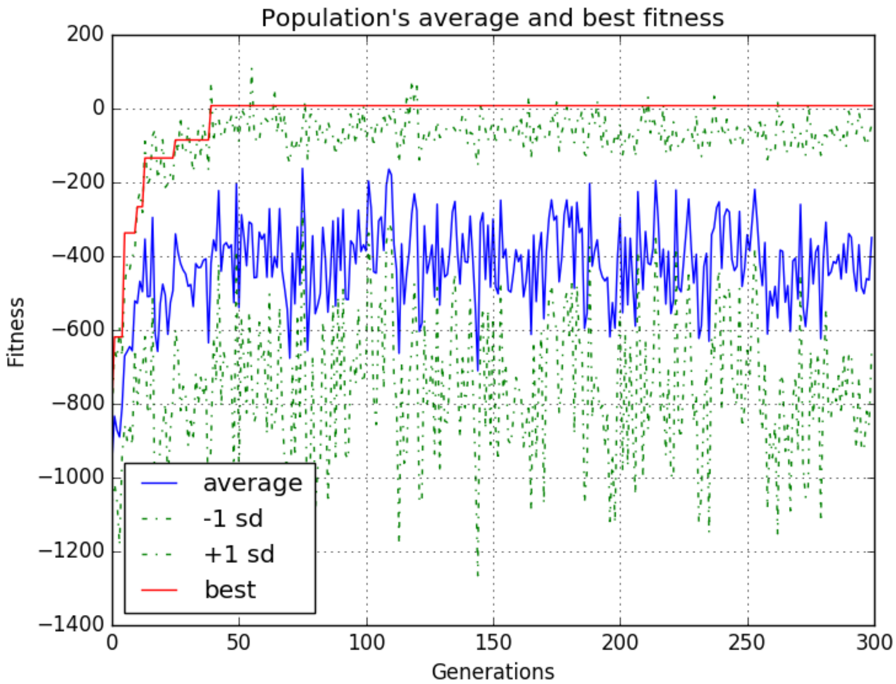


Figure 4.24: Test 5 - NEAT Fitness graph
The best solution was found in generation 31. A step climb in best fitness early along with average fitness. But 250 generations later still no improvment.

Chapter 5

Discussion

The first test (Figure: 4.4) was the only test that resulted in NEAT vastly outperforming both BFS and A*star. NEAT is able to take into account amount of turns, where A*star used manhattan distance as a heuristic which makes a vertical step and a horizontal step equal in distance. The shortest path generated by BFS and A*star created a stair-shape which resulted in a lot of turns, getting less fitness, even tho the path is equally long.

In the second test (Figure: 4.8) all algorithms got very similar fitness even though they have distinct solutions. The NEAT solution was found very quickly, but was unable to correct its error of having a unnecessary turn within the session. This could be a result of a poorly designed fitness function that does not punish turns enough.

In the third test (Figure: 4.11) all algorithms produced the same, optimal, result. This is interesting because there are multiple optimal solutions to this problem. BFS and A*Star both goes through all possible orderings of wires and uses the one that generated the best fitness, it is pure chance that NEAT created the exact same solution.

In the fourth test (Figure: 4.16), NEAT was not able to perform at A*star and BFS level. For many generations, NEAT refused the path the green wire to its destination. Instead it insisted of shortening the wire length. This is unwanted behaviour that could be a result of poorly designed fitness function. As the fitness function is written now, wires get punished while pathing until the destination is reached. Only on arrival does the fitness increase. Adding more parameters, such as distance to destination, might have resolved some of these situations, but could also create other unwanted behaviours such as pathing a wire straight ahead as close to its destination as possible. The extra bits of wire seen in figure 10 on the green and purple wires could be a result of NEAT sets up a priority order to move and without further analysis of the input these bits are required.

In the fifth test (Figure: 4.18 - 4.24), NEAT was not able to compete with A*star or BFS. The size of the grid in this test was larger than previous test and wires had long way to path. Since pathing is punished by the fitness function NEAT opted to minimize wire length instead. This resulted in NEAT having a hard time solving the problem.

5.1 Pathing choice

Since the neural network do not have the option of doing no move at all a wire the can move always will. Because wire length is punished by our fitness function NEAT seem to prefer to minimize wire length by moving itself into a corner to cut out possible moves as can be seen in figure 4.11. Figure 4.23 it seems like another wire cuts of another to minimize wire length. This could be the result of a poorly written fitness function.

The low number of hidden inputs generated via NEAT indicates that not much analysis of the input are being made. Input are usually connected directly to output with no in between nodes. Since the highest rated action is not always chosen (in the case that it is illegal) so the network wish to go one way but it goes another, if that happens to be the right way it gets rewarded for attempting to go the wrong way. This indicates that NEAT creates an internal priority list of moves for each wire. A priority list is enough to wire small grids but more analysis is required for larger grids.

Chapter 6

Conclusion

Todo..

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