Effects of Changing Specific Parameters in a Machine Learning Algorithm for a Car Simulation

Abstract

In this study, I explored the influence of altering car size parameters within a machine learning algorithm for a car simulation environment. Through systematic manipulation of the car size variables (50, 75, and 100), I observed distinct patterns in survival rates across thirty generations. The results indicate that car size significantly affects the survival rate, with size 75 demonstrating a balanced and consistent survival rate throughout the generations.

Background

As of recent years, the realm of car simulations has undergone a remarkable transformation, owing substantially to the advancements in machine learning technologies. These simulations are no longer confined to simple rule-based systems but have expanded to incorporate deep learning and neural networks, providing more nuanced and realistic behaviours in simulated environments. The integration of machine learning into car simulations has paved the way for a new frontier in autonomous vehicle development, allowing for robust testing and training environments that can mimic real-world scenarios with high fidelity. Leveraging machine learning, simulations can now assimilate complex driving environments and traffic scenarios, providing a sandbox for the development of smarter, safer, and more efficient autonomous vehicles.

Purpose

The primary aim of this study is to unravel the intricate relationships between specific parameter adjustments in machine learning algorithms and their subsequent impact on car simulation performance. By scrutinising how these parameter modifications influence various aspects of the simulation, I aspire to craft a blueprint for optimising machine learning algorithms within this domain. The parameter I will be adjusting in this experiment is the size of the car, as to observe if that factor influences the cars performance in any way.

### Methodology

#### Overview of the Current Code

The existing code serves as the foundation of our car simulation platform, integrating both machine learning elements and dynamic vehicle modelling. Predominantly, the code utilises a deep neural network (DNN) to facilitate the learning process, wherein the network adapts through numerous iterations to optimise the car's navigation capabilities within the simulation environment. The machine learning elements are pivotal in enabling the car to learn and adapt to these conditions, enhancing its decision-making capabilities and overall performance.

#### Hypothesis

As the size of the car increases, the population of members that survive each generation will become lower

#### Independent Variables

- CAR\_SIZE\_X (Car Width)

- CAR\_SIZE\_Y (Car Height)

#### Dependent Variables

Amount of Surviving Members

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Generation

#### Controlled Variables

- Map (map.png)

- Class attributes and methods

- Amount of members in each generation

#### Experimental Procedure

1. Run the control group (the original program with the intended car size) until it reaches Generation 30 and record the amount of cars that survived in each generation
2. Alter the CAR\_SIZE\_X and CAR\_SIZE\_Y variables by an increment of 25
3. Run this altered program until Generation 30 and record the amount of cars that survived each generation
4. Repeat Step 2 and then Step 3

#### Data Analysis

The data will be visually represented through a line graph where each line will be a different group. The x-axis will show each generation until Generation 30 and the y-axis will show the amount of cars that survived.

### Results

#### Tabulated Data

|  |  |  |  |
| --- | --- | --- | --- |
|  | Amount of Surviving Members/Generation | | |
| Generation | Size: 50 | Size: 75 | Size: 100 |
| 1 | 0 | 1 | 0 |
| 2 | 0 | 2 | 0 |
| 3 | 2 | 4 | 0 |
| 4 | 2 | 7 | 1 |
| 5 | 7 | 7 | 2 |
| 6 | 11 | 12 | 3 |
| 7 | 12 | 6 | 4 |
| 8 | 12 | 16 | 8 |
| 9 | 11 | 12 | 6 |
| 10 | 9 | 8 | 9 |
| 11 | 12 | 12 | 10 |
| 12 | 12 | 20 | 11 |
| 13 | 8 | 10 | 11 |
| 14 | 8 | 16 | 13 |
| 15 | 13 | 14 | 15 |
| 16 | 13 | 12 | 18 |
| 17 | 11 | 14 | 15 |
| 18 | 12 | 20 | 11 |
| 19 | 9 | 17 | 13 |
| 20 | 12 | 15 | 13 |
| 21 | 9 | 11 | 6 |
| 22 | 12 | 18 | 8 |
| 23 | 10 | 15 | 10 |
| 24 | 10 | 15 | 11 |
| 25 | 16 | 14 | 15 |
| 26 | 11 | 13 | 19 |
| 27 | 13 | 16 | 11 |
| 28 | 13 | 15 | 15 |
| 29 | 11 | 12 | 17 |
| 30 | 16 | 15 | 13 |

#### Graphs



### Discussion

#### Interpretation of Results

Car size 75 generally exhibits a higher survival rate compared to size 50, especially in the middle generations. The car size of 100 seems to struggle initially with no survivors in the first few generations, but it starts showing improvement from generation 4 onwards and tends to catch up with the other sizes in later generations, even surpassing size 50 at several points. The survival rate for all sizes seems to stabilise after initial fluctuations, indicating possible optimisations or adaptations occurring within the simulation. There are peaks and troughs in the survival rate across generations, which might be the result of various factors such as changes in environmental conditions, competition, etc.

* **Car size 75** seems to offer a balanced approach with a generally high survival rate throughout the generations.
* **Car size 100** shows potential, especially in the later generations, indicating that it might be beneficial for longer-term survival.
* **Car size 50** has the lowest survival rate initially but demonstrates adaptability and improvement over time.

#### Limitations

The limited frame rate of the recording software may impact the results when considering that a car could’ve died off frame and there would be no way to account for it.

### Conclusion

The variable car size significantly influenced the survival rates in the simulated environment. The data demonstrated that a car size of 75 yielded a generally higher survival rate, showcasing a balanced approach between adaptability and resilience across generations. Conversely, size 50, despite a rocky start, showed a gradual increase in survival rates, hinting at a potential for adaptability. Meanwhile, size 100, although initially struggling, displayed a promising upward trend in the later stages. These findings highlight the pivotal role of car size in optimising machine learning algorithms for more realistic and effective car simulations.