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Deep Learning Approach Towards T-Rex Game

Abujar Shaikh[1*], A.K. Sampath[2], Anupam Choudhary[3]

[1,2,3]Dept of Computer Engineering, Rizvi College of Engineering, Mumbai University, Mumbai, India

[*]*Corresponding Author: abuzar@eng.rizvi.edu.in Tel.: +91 9892873188*

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Abstract— In this project, we enforce both feature-extraction based totally algorithms and an end-to-cease deep reinforcement mastering technique to discover ways to control Chrome offline dinosaur recreation directly from high-dimensional sport display input. Results display that as compared with the pixel function based totally algorithms, deep reinforcement learning is more effective and effective. It leverages the high-dimensional sensory input immediately and avoids capability errors in characteristic extraction. Finally, we recommend special schooling strategies to address class imbalance issues due to the boom in game velocity. A simple and smooth GUI is supplied for smooth gameplay. The gameplay layout is so simple that user won't discover it tough to use and understand. Different images are used within the development of this easy recreation project, the gaming environment is similar to the authentic T-Rex Dino Run sport. In order to run the project, you need to have set up python and pygame in your PC. This might be a new word for many however each and every one of us has learned to stroll the usage of the idea of Reinforcement Learning (RL) and this is how our brain still works. A reward gadget is a foundation for any RL algorithm.

Keywords—Deep reinforcement, Sensory input

I. INTRODUCTION

Machine Learning is basically a subsystem in the large era of the internet in Artificial Intelligence. The purpose of this article is to give you an introduction to artificial intelligence, by discovering in particular two algorithms that are widely used in the field. I will voluntarily simplify some explanations of these algorithms, which can sometimes quickly become complex. The main interest is to show you how they work in general so that you will no longer be lost when you hear something about machine learning, a field that is increasingly being used nowadays. I think the best way to explain it to you is through concrete examples of use. The idea of this AI that we are going to create is to learn to play by watching my own games. I am going to play the game myself, and recording my decisions. The AI will have the intelligence to be able to make decisions at any time (with a Neural Network algorithm), and we will use an algorithm to make its intelligence similar to my decisions (Genetic Algorithm).
Well, that also means we have to be good at the game, if we are bad, so will the AI. No need to have previous knowledge of AI to understand this game, nor of programming: maybe just logic or mathematical mind. We try explain to you how we made an Artificial Intelligence to play the game T-Rex game. T-Rex is an in-build integrated game on the Google Chrome browser, which appears when you do not have internet. The goal is simple, you need to control a dinosaur with your keyboard up, down keys where you must avoid the obstacles that appear by jumping.

The recreation may be launched within the Chrome browser on both computing devices and mobile. The manipulate is the simplest: while you see that black dinosaur to your browser signifying that there's no Internet connection, simply hit the spacebar to launch the recreation. The spacebar is likewise used to leap over obstacles. The down arrow is used to duck. If you're on the mobile, just faucet the little Chrome Dino to get into movement and keep away from obstacles, too.

II. RELATED WORK

In past years, we have seen that when we got stuck to the website, we see a screen displaying troubleshooting unable to connect to the internet in Google Chrome. In 2013, Google Deep mind proposed the use of deep reinforcement studying models to play the games when we are not connected to the internet. Taking just the pixels from the object and user inputs, they were capable of attaining human-expert performance to the output. The main gain of Deep-Q getting to know is that no specification of the user input is wanted despite the high dimensional image input. The agent is capable of discovering ways to play the game without knowing the underlying recreation logic. To procedure the image data, they use a deep Q-network (DQN) to directly evaluate the Q feature for Q-gaining knowledge of. An enjoyable replay is also implemented to de-correlate experiences. This framework is model-unfastened and can generalize to numerous comparable problems. After their research, many papers tried to make improvements. Further improvements involve prioritizing enjoy replay, extra efficient schooling, and better stability

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when education [2]. But It used a model-unfastened TD-studying algorithm just like Q-studying and performed human expert-level overall performance [4]. Since then, the use of reinforcement getting to know has popularized and various attempts have been made to use reinforcement gaining knowledge of on games.

III. METHODOLOGY

1. Baseline:
We examine our Deep Q-gaining knowledge of methods and MLP supervised getting to know techniques with the following three baselines.

- Keep-Jump: Keep-Jump is a naive version wherein the agent keeps jumping irrespective of its distances from the barriers nor the attributes along with the peak and width. This baseline represents the performance of those agents without artificial intelligence over the game.
- Human Optimized Approaches: Given the capabilities extracted from the game image, we put into effect one baseline imitating the human gamers, where the T-Rex jumps every time the first impediment is close enough (much less than 2 hundred pixels). This baseline follows the intuitive grasping player strategy. Its handiest considers the closest obstacle at the screen.
- Human Player Records: We invite some experienced players who hold statistics of 1000 points in T-Rex video games and ask them to compete with our agents. In this way, we may want to see extraordinary decision-making procedures between humans and AI in addition to their performance.

2. Online Learning MLP:
In this section, we examine the results of the MLP model. Given a list to research the optimized leaping position, we found the average scores quit to boom over 900 rounds iteration. In addition to the deviation of the image processor, we agree with the overpowering computation over parameters in a fully-connected network undermines the performance as well. To aid it, we behavior a similar experiment with less limitation information. Illustrated in Fig (b), as the model reaches the target it tries to jump to get the score high.

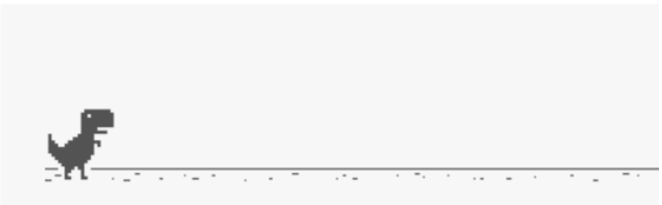

Fig (a): Steady model of Dinosaur

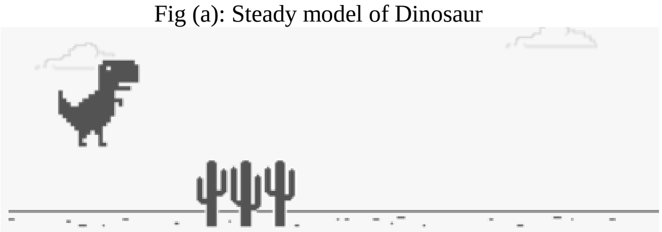

Fig (b) Dino detects the position of cacti

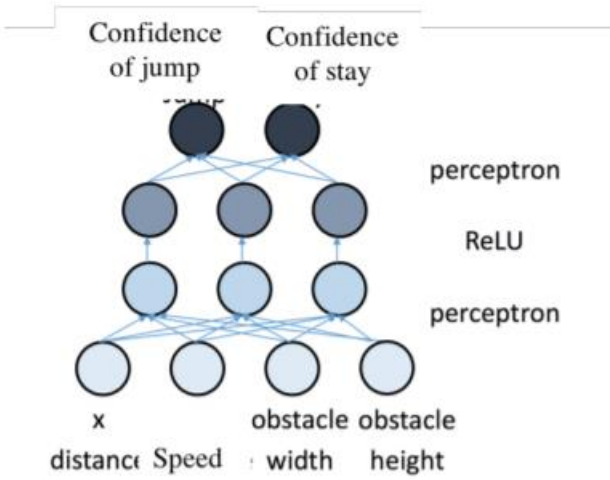

Fig 1. Structure of Multi-Layered Perceptron Model

3. Multi-Layered Perceptron:
We recommend a web studying Multi-Layered Perceptron (MLP), which takes the pixel-primarily based totally functions as input to expect the optimized leaping function beforehand of the boundaries. In this work, we leverage the pixel-primarily based totally functions extracted with the aid of using our photograph process or the usage of OpenCV, such as the statistics of a listing of boundaries in the front of the agent. For an unmarried obstacle, including a cactus, we extract at least4 functions, such as 1) its distance from the agent, 2) its height, 3) its width, and 4) the relative speed The functions then undergo a multi-layered perception community which conceives choices approximately whether or not to jump or live at the floor below modern-day circumstances. We use on-line education to enhance the overall performance of MLP. When the agent hits boundaries even as leaping, we expect it ought to have jumped beforehand of the location in which it takes off. Comparatively, whilst the agent hits boundaries even as dropping, we infer there ought to be a put off in the modern-day leaping and the agent ought to have stayed at the floor at the modern-day leaping In addition, if the agent crashes into the boundaries even as staying at the floor, we expect it ought to have jumped at the ultra-modern movement.

4. Deep Q-Learning:

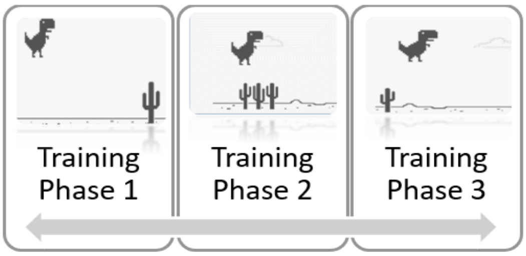

Fig 2. Deep Q-Learning Model

In traditional exploit-exploration techniques for Deep Q-learning, cost decreases overtime to make sure the agent

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explores extra states at the start stage under a large and then regularly lower the to make sure the final online policy converges to the most efficient policy. However, due to the fact, our T-Rex sport accelerates regularly and the agent needs to deal with distinct speed modes in a single round of the game, the normal training technique for Deep Q-studying has some problems. This may be explained via our mastering curve proven in Figure 2 Firstly, while we use the normal training method (shown in TRAINING PHASE I, with blue history in Figure 2), the learning curve flattens after 1. three million turns of training, in which the common of 20 check turns is about 750 and max rating of 20 rounds is one thousand. The error analysis suggests that beneath maximum cases, the T-Rex dies due to the random actions (Even though our price starts off evolved from a small cost of 0.1). As is explained in the preceding section, this is because the agent cannot control itself even as jumping. So even a small will result in T-Rex's random jump. Once it jumps, the agent loses the ability to control, and is probable to run into the adjoining obstacles beneath instances with high velocity. To remedy this problem, we introduce a TRAINING PHASE II. We make the equals zero, meaning no exploration. Then the performance of our algorithm continues to grow and reaches an average score of 1000 and a max score of 2000 for 20 take a look at turns.

Table (a).Comparison between different models

Algorithm	Average 20	Maximum	Standard
Keep-Jump	41	111	23
Human-expert	910	1500	420
Human-optimized	196	4670	134
MLP	469	1335	150
Deep Q-learning	1216	2501	678

This training approach in large part increases the overall performance of our algorithm and makes the common rating a 25% increment. The maximum score additionally reaches the 2500 points with an increment of 500 factors. As a result, the performance of our set of rules after three training levels is better than human experts.

IV. RESULTS

In this research, we have seen that the T-Rex game can be played with different approaches. In Online MLP, we have seen that when the game is played online Dino tries to score by jumping from the obstacle and makes a high score. Similarly, in the Multi-Layered Perceptron, we first calculate the distance(x) and speed(y), and then we try to decide whether to jump or stay to make a high score. And Finally, In Deep Q-Learning Model, we have seen that we got the most appropriate result an optimized model to play the T-Rex game. In the Deep Q-Learning model is this divided into three phases the First Training Phase, Dino tries to see the obstacle, and tries to reach the obstacle. In the Second Training phase, it jumps from the obstacle and finally, it jumps in the third phase. From all the results we have seen that to get the best approach to play the T-Rex is in Deep Q-Learning Model because it saves time and getting a high score is easily achieved compared to other models.

V. CONCLUSION

Thus, we can conclude from the results that the deep learning approach is the best to attain the play of the Chrome Offline Dinosaur Game. For the feature extraction primarily based algorithm, pc model methods can recognize the T-Rex and limitations from the images. Carefully designed characteristic extraction algorithms can efficiently abstract the performance and deep learning constructed upon them can improve its overall performance notably as compared with the naïve baseline. MLP discovered from online training can strengthen the AI in addition to it refines the parameters automatically via experience. However, the characteristic-extraction based totally algorithm has its limits and cannot outperform human experts. For the end-to-end Deep-Q learning method, our result shows that it can correctly play the game through getting to know the straight from the pixels without characteristic extraction, and is much stronger than the function-based totally approach. Finally, a specially designed Deep Q-learning method can assist us to conquer the difficulties of our game, which similarly improves our AI's performance for the deep learning approach and helps obtain human results for getting the best possible output from our given input.

REFERENCES

[1]https://thenextweb.com/dd/2018/09/07/4-years-later-google finally-explains-the-origins-ofits-chrome-dinosaur-game/

[2]V. Mnih, K. Kavukcuoglu, D. Silver, A. Graves, IAntonoglou, D. Riedmiller. Playing Atari with deep reinforcement learning. arXiv preprint arXiv:1312.5602, **2013**.

[3] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M.Riedmiller, A. K. Fidjeland, G. Ostrovski, et al. Human-level control through deep reinforcementlearning. Nature, 518(7540):**529**–**533**, **2015**.

[4] G. Tesauro. Temporal difference learning and td-gammon. Communications of the ACM,38(3):58–**68**, **1995**.

[5] G. Bradski et al. The opencv library. Doctor Dobb Journal, 25(11):**120**–**126**, **2000**.

[6] Koray Kayabol, Member, IEEE "Histogram-Based Contextual Classification of SAR Images", IEEE geoscience and remote sensing letters, vol. **12**, no. **1**, January **2015**.

[7] Xin Su, Chu He, Member, IEEE, Qian Feng, Xinping Deng, and Hong Sun, Member, IEEE "A Supervised Classification Method Based on Conditional Random Fields With Multiscale Region Connection Calculus Model for SAR Image",IEEE geoscience and remote sensing letters, vol. **8**, no. **3**, May **2011**.

[8] Mery Picco and Gabriela Palacio "Unsupervised Classification of SAR Images Using Markov Random Fields and G0 I Model",IEEE geoscience and remote sensing letters, vol. **8**, no. **2**, March **2011**.

[9] A. Sharma, P.K. Misra, "Aspects of enhancing security in software development life cycle," Advances in Computational Sciences and Technology, Vol. **10**, Issue. **2**, pp. **203-210**.

[10] Jr. Padal, C.M. Salado, L. Mary Jean May, N.P. Sobejana, "SPAMAST Smart Garbage Bin Monitoring System Using

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Wireless Sensor Network," Journal of Engineering Research and Reports, pp. **1-16**, **2019**.

[11] D. Goel, R. Upadhyay, "Effectiveness of use of Animation in Advertising: A Literature Review," International Journal of Scientific Research in Network Security and Communication, Vol.**5**, Issue. **3**, pp. **146-159**, **2017**.

AUTHORS PROFILE

Mr. Abujar Shaikh currently pursuing Bachelor of Computer Engineering from University of Mumbai, India.He has done a extra courses of Python in college. His main interest is in Machine Learning,Image Processing and Artifical Intelligence. He is currently pursing an ethical hacking course in udemy.He is Keen in technology and had an internship projects virtual for a Hutflick In his WDL project he had done a survey on a coaching class and provided them a free website for student's over there to get their update timetable daily.He was done very good research projects in past.

Mr. Dr. A.K Sampath is an assistant professor.He has done a PHD. in Machine Learning and Artifical Intelligence.He has 12 years+ experience in teaching and he had done many research in machine learning and artifical intelligence, image processing, mobile computing, cryptography and network security.He has done many hackathons.He has given best research and provide good quality of education to the students.He very helpful to the student for their research projects.

Mr. Dr Anupam Chaudhary is an assistant professor.He has done his P.H.D.His main research interest area are Compilers, Advanced Networking, Embedded system, Advanced database, AI, ANN, Robotics, Cognitive radios, Image Processing, Digital signal processing, VLSI, Biomedical application developements, Sensor technologies, Biosensors, Nanotechnology. He his very helpful to the students and help students to achieve their desire goals in their life.Students of him are great achieve in their life.

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