IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 25, Issue 3, Ser. II (May. – June. 2023), PP 01-05
www.iosrjournals.org

Deep Learning And Artificial Intelligence For Games

Prof. Pratima Kadam[1], Mr. Neel More[2], Mr. Ketan Barahate[3], Mr. Kunal Nagare[4] and Mr. Ketan Borse[5]

[1]Prof. Pratima Kadam, Bharati Vidyapeeth's College Of Engineering, Lavale, Pune.
[2] Mr. Neel More, Bharati Vidyapeeth's College Of Engineering, Lavale, Pune.
[3] Mr. Ketan Barahate, Bharati Vidyapeeth's College Of Engineering, Lavale, Pune.
[4] Mr. Kunal Nagare,Bharati Vidyapeeth's College Of Engineering, Lavale, Pune.
[5]Mr. Ketan Borse, Bharati Vidyapeeth's College Of Engineering, Lavale, Pune.

Abstract

Deep learning, a branch in artificial intelligence is a product of modern computing that has been used to develop solutions to a range of problems. Is has been used to earlier detection of cancer cells in human body to self-driving cars. More recently it has been used to create art itself, which had been associated with humans, as a result of complex thinking processes a human mind goes through. Deep learning focuses on the neural pathways resembling human brain neurons to communicate and process information and arrive at a better and faster resolution of the problem, much faster than a human brain can perceive. In this study we will look at the deep learning neural networks that being used in developing computer games that simulates real world possibilities and we will also look at the break throughs in artificial intelligence or AI technologies that made it possible.

Date of Submission: 08-05-2023 Date of Acceptance: 18-05-2023

I. Introduction

Deep learning has been around for a very long time, though not by that name. Cybernetics has evolved during the early of 20th century. In fact it was first defined by Norbert Wiener in his book in 1948 by the same name "Cybernetics" as a study of control and communications in animal and machine. Around the same time as cybernetics was being developed "Connectionism" by Thorndike was also picking up pace, his theory was a classic example that examined human adult learning using mathematics, spelling and reading. His theory also focused on animal behaviour such as a cat learning to escape from a box by moving a lever inside the box. Then Deep learning came along in 2006 with a Deep Belief Networks (DBN) by Geoffrey Hinton who used Greedy layer-wise training [5].Deep learning as we know today has evolved into a very high performing approach to machine learning. It can be used in a variety of applications. It has increased accuracy compared to other similar approaches for tasks like Language translations and Image

Recognition. Neural networks mimic the human brain, here we don't need to explicitly program everything. In the last couple of decades the amount of data being produced everyday due the usage of internet has hyped up the term "deep learning" as high processing power has also being achieved to process the data without any human supervision consequently, machine learning and deep learning are leaning more and more into the picture.

II. Content:

Deep learning term as first weaved into machine learning networks by Geoffrey Hinton described a model in which the top two layers formed an undirected associative memory and the rest of the hidden layers form a directed acyclic graph that converted the representations in associative memory to observable variables such as pixels of an image data. The model had some attrative features as stated by the author:

1. A fast, greedy algorithm was in place that could search for a good set of parameters quickly, and even in deep networks having millions of parameters and many hidden layers.
2. The algorithm was unsupervised but could be applied to labeled data by learning a model that generated both label and the data.
3. The tuning algorithm did great in generative model which outperformed discriminative methods on the hand-written digits dataset.
4. It made easier to interpret the distributed representations even in deep hidden layers.

It was a successful example of greedy layer-wise training of networks that allowed quite more layers into the feedforwardnetworks[1].

With AI, games have been able to deliver a better experience to gamers. Creating life-like environments as progressions are made into the game. Complexities in games that uses AI ensures players are completely endulged into the game. Along with developments in the games various gaming devices have also made their way into the market, so that gamers can have overall more immersive experience across various devices.

AIs have been used to provide several functionalities in games such as[2]:

NPCs
Pathfindings
Decision-making
Data mining
Procedural content generation
Player experience modeling
Cheating

Most popular and well-known Deep learning capabilities used in games are as follows[3]:

Convolutional Neural Networks -

Convolutional Neural Networks can be trained seeminglessly on large datasets and can still deliver desired level of accuracy. As CNNs tends to work well in generalizing new data. CNNs are efficient when it comes to images and video processing. This is possible because they can be parallelized on GPUs, that may result in faster training times.

CNN with reinforcement learning algorithms can lead to development of games that can be more realistic and engrossing for users since AI may achieve abilities to learn from mistakes and perform corrections and eventually get better over time.

Recurrent Neural Network (RNN)

Here we can explore the potential for designing more realistic and believable characters, efficient game mechanics, and increased immersion.

- Realism in Characters: RNN could be applied to emulate and learn from human behaviour, emotions, and expressions. This allows developers to generate more belieable digital characters.
- Improved Game mechanics: RNN can configure itself to optimize gameplay simply by understanding player behaviours and preferences. Here the developers can potentially utilise the following data to improve gaming experience such as designing or opponent AI.
- Immersion Amplification: This architecture of network may allow game AI to respond dynamically to player inputs, giving away a more fluid experience throughout. Subsequently giving NPCs more realistic reactions, users may be more motivated to operate in the gaming environment.

Long Short-Term Memory Networks (LSTM)

It is a type of neural network that can learn from sequence data. Thus, these are ideal for handwriting recognition machines with translation problems, where the inputs denotes series of actions over a time-period.

LSTM have also been known to be effective at modeling text data, and can therefore take up tasks such as Natural language processing. As these can retain data for a long period of time LSTM could find implementations in Memory based games.

Deep Q-Networks

Deep Q-Networks provides pathway to scale across autonomous gameplay, for example – One can design control policies for agents withing the game. Like our player is trying to tread through couple of obstacles, In that case Deep Q-Networks can be trained to allow user to perform actions that maximize user reward (i.e. increase gained score). Also using Deep Q-networks to generate NPCs with realistic behaviours.

-Developing control policies: Developing control policies for NPCs or the player character itself could include traning a Deep Q-Network agent such that it receives end-to-end raw pixel data and maps them directly to available action output probabilities.This method will allow nonlinear function approximation, that might resolve in successful generalization across many environments.

-Generating NPC behaviours: Training the DQN on set of inputs and available actions available in the given set of environment. By consolidating this approach, NPCs can display more realistic behaviour and could be accounted for a bigger difference in the elements of the environment.

-Pathfinding Algorithms: To find an optimal path we have Djikstra's algorithm; however through this algorithm we cannot guarantee an optimal path, like the effect of missing out on a fix point in game while navigating. A DQN could be used to find optimum path by putting in the current game state and actions available to perhaps gain a probability for each output. By implementing DQN while player traverse through the environment could allow us to consider different environmental factors or elements when finding a path, leading to a more fluid movement.

A study done to compare DQN with some of the best learning methods from reinforcement learning on 49 games, resulted DQN outperforming the best reinforcement learning methods on 43 of the games without any prior knowledge being incorporated [4].

Reinforcement learning is a learning process for machines that uses sensory inputs from environments and past data stored in database ,which closely resembles how a human infant might learn about it's surroundings and act accordingly to achieve some goal. Whereas machines have some functions to maximize in order to shoot up their reward gain, in humans we associate achievin g a goal or target to dopamine spikes in neurons. Recent advances in training Deep Q-networks has allowed the machines to develop policies using high dimensional data through sensory inputs while integrating end-to-end reinforcement learning. Being applied to various types of games the agent was able to achieve a high scores comparable to that of a professional human game tester. A research done to develop an agent to achieve a wide range of tasks competently, involved designing a Deep Q-network that encorporated reinforcement learning with artificial neural networks was successfully able to allow artificial neural network to learn policy about object categorization directly from raw sensory data. These convolutional neural networks build on top of each other builds up abstract representation of data progressively to give out a distinct outcomes to take further actions upon. The author utilises an parameterized approximate value function $Q(s,a;\theta_i)$ using deep convolutional network[4]. Here θ_i is the parameter of weight for the Q network iteration for i^{th} iteration. To store the agent's experience for further optimization $e_t = (s_t,a_t,r_t,s_{t+1})$ is used at every step t in the data set $D_t = \{e_1,...,e_t\}$. The model uses the given loss function to minimize making decisions:

$$L_i(\theta_i) = E_{(s,a,r,s')\sim U(D)}[(r + \gamma \max Q(s',a'; \theta_i^-) - Q(s,a;\theta_i))^2]$$

where, γ is the factor determining the agent's horizon, θ_i is the parameter for Q-network at i iteration and θ_i^- are the network parameter used to computer the target at iteration i. The target net-

work parameters θ_i^- are only updated with the Q-network parameters (θ_i) every C steps and are held fixed between individual updates.

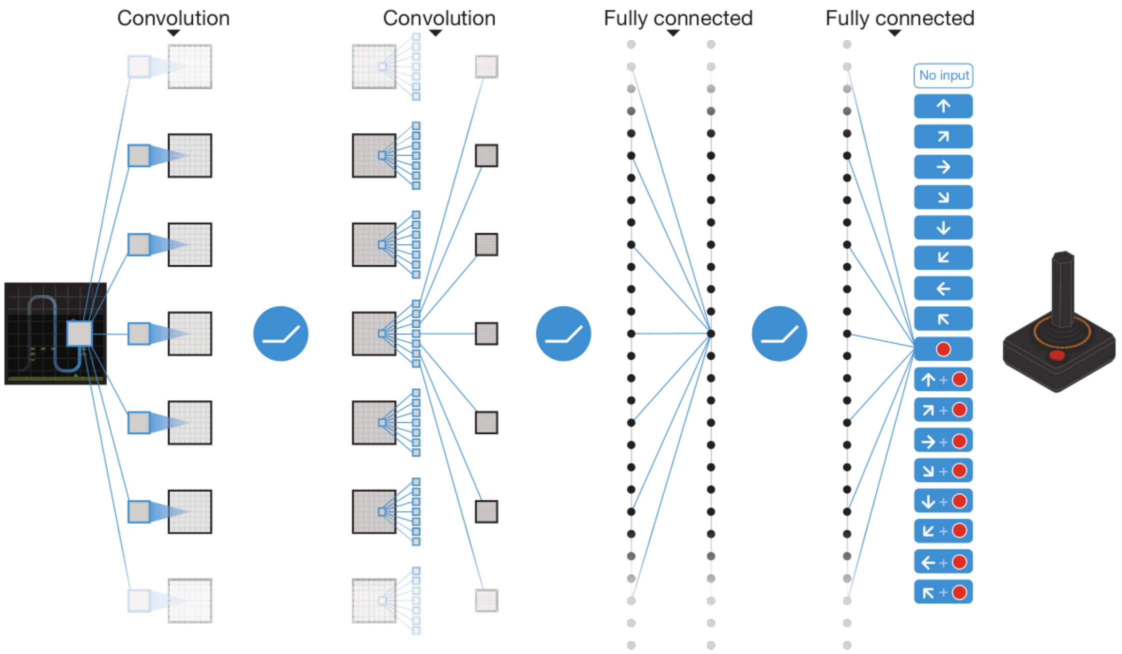

Figure 1. | Illustration of the convolutional neural network.

The input to the neural network consists of an 84 X 84 X 4 image produced by the preprocessing map ϕ, followed by three convolutional layers (note: snaking blue line symbolizes sliding of each filter across input image) and two fully connected layers with a single output for each valid action. Each hidden layer is followed by a rectifier nonlinearity (that is, max(0,x)).[4]

III. Conclusion:

The resulting comparisons from obtained DQN agents with methods used in literature and a professional human game tester displays as[4]:

Game	Random Play	Best Linear Learner	Contingency (SARSA)	Human	DQN (± std)	Normalized DQN (% Human)
Alien	227.8	939.2	103.2	6875	3069 (±1093)	42.7%
Amidar	5.8	103.4	183.6	1676	739.5 (±3024)	43.9%
Assault	222.4	628	537	1496	3359(±775)	246.2%
Asterix	210	987.3	1332	8503	6012 (±1744)	70.0%
Asteroids	719.1	907.3	89	13157	1629 (±542)	7.3%
Atlantis	12850	62687	852.9	29028	85641(±17600)	449.9%
Bank Heist	14.2	190.8	67.4	734.4	429.7 (±650)	57.7%
Battle Zone	2360	15820	16.2	37800	26300 (±7725)	67.6%
Beam Rider	363.9	929.4	1743	5775	6846 (±1619)	119.8%
Bowling	23.1	43.9	36.4	154.8	42.4 (±88)	14.7%
Boxing	0.1	44	9.8	4.3	71.8 (±8.4)	1707.9%
Breakout	1.7	5.2	6.1	31.8	401.2 (±26.9)	1327.2%
Centipede	2091	8803	4647	11963	8309(±5237)	63.0%
Chopper Command	811	1582	16.9	9882	6687 (±2916)	64.8%
Crazy Climber	10781	23411	149.8	35411	114103 (±22797)	419.5%
Demon Attack	152.1	520.5	0	3401	9711 (±2406)	294.2%
Double Dunk	-18.6	-13.1	-16	-15.5	-18.1 (±2.6)	17.1%
Enduro	0	129.1	159.4	309.6	301.8 (±24.6)	97.5%
Fishing Derby	-91.7	-89.5	-85.1	5.5	-0.8 (±19.0)	93.5%
Freeway	0	19.1	19.7	29.6	30.3 (±0.7)	102.4%
Frostbite	65.2	216.9	180.9	4335	328.3 (±250.5)	6.2%
Gopher	257.6	1288	2368	2321	8520 (±3279)	400.4%
Gravitar	173	387.7	429	2672	306.7 (±223.9)	5.3%
H.E.R.O.	1027	6459	7295	25763	19950 (±158)	76.5%
Ice Hockey	-11.2	-9.5	-3.2	0.9	-1.6 (±2.5)	79.3%
James Bond	29	202.8	354.1	406.7	576.7 (±175.5)	145.0%
Kangaroo	52	1622	8.8	3035	6740 (±2959)	224.2%
Krull	1598	3372	3341	2395	3805 (±1033)	277.0%
Kung-Fu Master	258.5	19544	29151	22736	23270 (±5955)	102.4%
Montezuma's Revenge	0	10.7	259	4367	0 (±0)	0.0%
Ms. Pacman	307.3	1692	1227	15693	2311(±525)	13.0%
Name This Game	2292	2500	2247	4076	7257 (±547)	278.3%
Pong	-20.7	-19	-17.4	9.3	18.9 (±1.3)	132.0%
Private Eye	24.9	684.3	86	69571	1788 (±5473)	2.5%
Q*Bert	163.9	613.5	960.3	13455	10596 (±3294)	78.5%
River Raid	1339	1904	2650	13513	8316 (±1049)	57.3%
Road Runner	11.5	67.7	89.1	7845	18257 (±4268)	232.9%
Robotank	2.2	28.7	12.4	11.9	51.6 (±4.7)	509.0%
Seaquest	68.4	664.8	675.5	20182	5286(±1310)	25.9%
Space Invaders	148	250.1	267.9	1652	1976 (±893)	121.5%
Star Gunner	664	1070	9.4	10250	57997 (±3152)	598.1%
Tennis	-23.8	-0.1	0	-8.9	-2.5 (±1.9)	143.2%
Time Pilot	3568	3741	24.9	5925	5947 (±1600)	100.9%
Tutankham	11.4	114.3	98.2	167.6	186.7 (±41.9)	112.2%
Up and Down	533.4	3533	2449	9082	8456 (±3162)	92.7%
Venture	0	66	0.6	1188	3800 (±238.6)	32.0%
Video Pinball	16257	16871	19761	17298	42684 (±16287)	2539.4%
Wizard of Wor	563.5	1981	36.9	4757	3393 (±2019)	67.5%
Zaxxon	32.5	3365	21.4	9173	4977 (±1235)	54.1%

Latest innovation in Artificial intelligence in gaming industry:

Cloud based gaming with AI

Cloud based gaming is a technology that allows streaming a game across internet in contrast to download the data on the machine to play. This technology has been around for a couple of years now but yet still have to see the mainstream.

Block-chain based gaming
Block-chain gaming is not a gaming phenomenon as of yet. Being a decentralised system it needs both gamers and developers to come together to get it into the crowd.

Voice or Audio recognition games
Using audio or voice recognition in gaming is certainly going to change we perceive gaming. Using voice command and so on, gamers would be able to control movements and other actions inside the game using just their voice.

Wearable support gaming and VR gaming
The recent innovations in wearable/VR gaming has raised the standards for immersive gaming making them more and more realistic and progressing towards entertainment.

Improved mobile gaming experience
Mobile gaming experience has evolved over the years a lot. It has gathered over massive number of gamers on mobile gaming platform, players are offered with a ton of mobile games available to them on their mobile phones. Phone companies have also been focussing on designing their phones around gaming fundamentals.

References:

[1]. Geoffrey E. Hinton, Simon Osindero, Yee-Whye Teh (A fast learning algorithm for deep belief nets)
[2]. Jeremy Dsouza (AI in gaming, Innovations changing the future of gaming) refer to (https://www.engati.com/blog/ai-in-gaming)
[3]. Anil Tilbe (Top 4 Deep learning algorithms for game development with use cases) refer to (https://levelup.gitconnected.com/top-4-deep-learning-algorithms-for-game-development-with-use-cases-e236d4faa4da)
[4]. Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A. Rusu, Joel Venesse, Marc G. Bellemare, Alex Graves, Martin Riedmiller, Andreas K. Fidjeland, Georg Ostrovski, Stig Petersen, Charles Beattie, Amir Sadik, Ioannis Antonoglou,Helen king, Dharshan Kumaran, Daan Wiestra, Shane Legg & Demis Hassabis
[5]. Jason Brownlee (What is Deep Learning ?) refer to (https://machinelearningmastery.com/what-is-deep-learning/#:~:text=Deep%20Learning%20is%20a%20subfield,ago%2C%20you%20may%20be%20confused.)