Discovering Missing Information in Quantum Theory via Deep Neural Network

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Abstract

In this study, we attempt to understand the bizarre behavior behind double-slit interference from the perspective of neural networks. Neural networks process signals through links that connect the particle and two slits, using graph theory and optimizing the internal hidden variable of network to obtain the relationship between input and output. Our modeling approach treats particles as input and the probability distribution of double slits as output. We hope to find the correlation between the real system and the neural network through visual deep learning to unveil the principles behind the mysterious veil limited by the uncertainty principle.

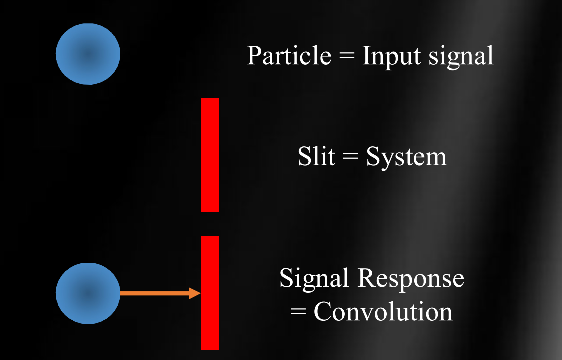
Keyword: hidden variable theory, double-slit experiment, deep learning

Goal and Introduction

The investigation of hidden variables can be traced back to 1935, when Einstein, leading the determinism, challenged the Copenhagen interpretation, led by Bohr, on quantum mechanics [1]. In 1964, Bell's inequality declared the non-existence of local hidden variables, but the exploration of the non-local hidden variables that account for the bizarre behavior of quantum mechanics is still an open question. The proposal of non-local latent variables, as in (a) the double-slit diffraction corresponding to Bohmian mechanics [2], and (b) quantum entanglement [3] attempted to solve with ER=EPR, and some teams even have used the wave function as a neural network to obtain the ground state solution [4].

In our research, we try to treat double-slit diffraction as a simple signal input response to the slits, and use graph theory to link the relationship to construct a neural.

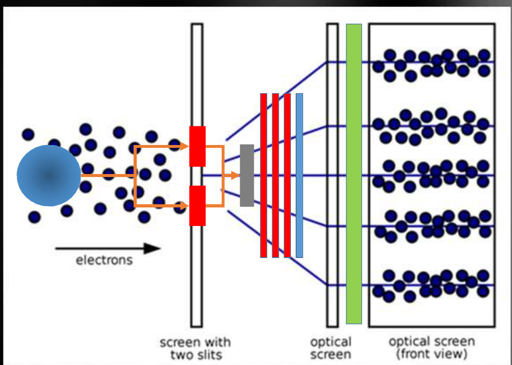
Method: Deep Learning for Probability



$$\int_{-\infty}^{\infty} f(\tau)g(x-\tau)\,\mathrm{d}\tau$$

Output signal　Input signal　Signal Response

Concatenate layer　Softmax layer　Fully connected layer

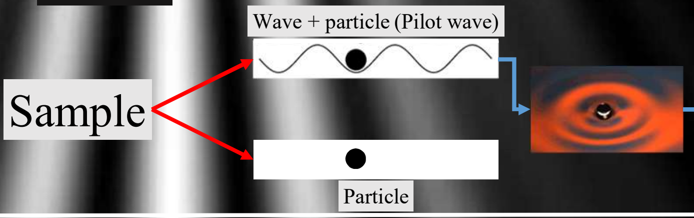


In the double-slit experiment, we can view the response of the signal between particles and the double slits as relying on the physical meaning of the convolution layer - the response of the system to the input signal. This response process can extract the internal hidden variables, allowing us to interpret the internal information transmission and even understand the movement of particles within the slits.

Result of de Broglie–Bohm Theory


David Bohm

In Bohm's theory, both wave and particle are viewed as a whole, with the wave playing the role of a one-way influence on the particle's motion, called the information/quantum potential. The potential is the key factor that causes the particle's motion to drift and produce interference fringes. In this case, we consider the presence of both particle and wave as quantum properties, while the absence of wave is considered as particle-like properties, with the former resulting in double-slit interference.

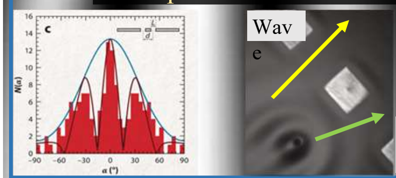


$$\Psi(x,t) = R(x,t)e^{iS(x,t)/\hbar}$$

$$\frac{\partial S}{\partial t} + \frac{(\nabla S)^2}{2m} + V - \frac{\hbar^2}{2m}\frac{\nabla^2 R}{R} = 0$$

Potential

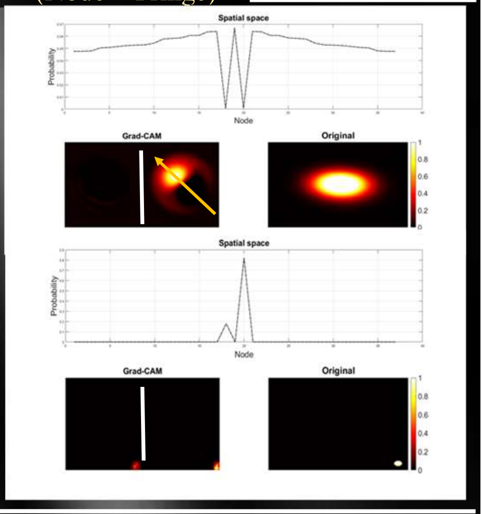
Experimental Result



During pilot-wave experiments using Bohmian mechanics, it was observed that particles tend to pass through only one slit, while the associated wave (which is seen as a potential) passes through both slits and creates diffraction stripes on the backside. In analyzing the behavior of deep learning networks, we utilize a technique called Grad cam to examine the focus of input components within the network. By utilizing a model based on Bohm mechanics, we are able to both reproduce experimental results and demonstrate both classical and quantum behavior.

Deep Learning Result (Node = Fringe)

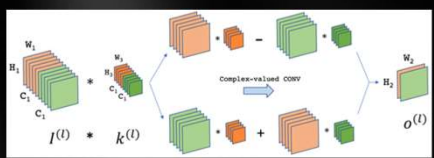
$$\frac{\partial R^2}{\partial t} + \nabla\cdot\left(R^2\frac{\nabla S}{m}\right) = 0$$



Future Work: Complex Value CNN [5], Copenhagen Interpretation

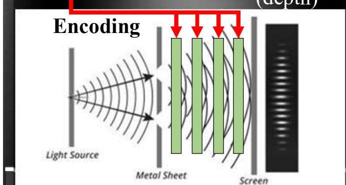
$$\Psi(x,t) = \frac{1}{\sqrt{2\pi\hbar}}\int_{-\infty}^{\infty} e^{ipx/\hbar}\Phi(p,t)\mathrm{d}p$$

Complex value Network



In the future, we will use complex-valued deep learning networks to analyze wave functions and repeat this experiment to obtain the complete wave function decomposition in double-slit diffraction.

Network　Encoding task: Layer (depth) to screen (depth)



Discussion

There is still much work to be done in the future, such as verifying the correlation between deep learning networks and real systems, which relies on encoding to connect the two. It also involves mapping the hidden variables of the neural network to the real space, which can provide a deeper understanding of the physical image within the neural network, such as arrival time of a quantum system.

Reference

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