# Alive: Interactive Visualization and Sonification of Neural Networks in Virtual Reality

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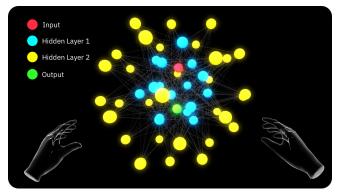


Figure 1. The *Alive* system, with the neural network at the center visualized as an interactive force-directed graph. **zhuoyuelyu.com/Alive** 

Abstract—Artificial Intelligence (AI), especially Neural Networks (NNs), has become increasingly popular. However, people usually treat AI as a tool, focusing on improving outcome, accuracy, and performance while paying less attention to the representation of AI itself. We present *Alive*, an interactive visualization of AI in Virtual Reality (VR) that brings AI "alive". *Alive* enables users to manipulate the parameters of NNs with virtual hands and provides auditory feedback for the real-time values of loss, accuracy, and hyperparameters. Thus, *Alive* contributes an artistic and intuitive way to represent AI by integrating visualization, sonification, and direct manipulation in VR, potentially targeting a wide range of audiences.

*Keywords*-artificial intelligence; virtual reality; humancomputer interaction; sonification; visualization;

## I. INTRODUCTION

AI has led to breakthroughs in areas such as image classification, object detection, and machine translation [1]. However, most research treats AI as a tool to accomplish tasks, focusing on boosting outcome and performance, with little attention paid to exploring the representation of NNs itself [2]–[5]. Meanwhile, the lack of transparency and interpretability of AI is a problem that needs to be addressed [6]–[8]. In this paper, we explore the concept of representing AI as a living being to uncover the inner workings of NNs in an experienceable way: it moves, changes colors, creates

sounds as training progresses, and even responds to the users' interaction with it.

To instantiate this concept, we present *Alive*, an interactive visualization that brings AI "alive", it leverages basic human sensory and motor activities: seeing, listening, and grabbing and moving objects for an intuitive, artistic, and enjoyable experience. Given the benefits of immersive analytics [9], [10], data visualization and sonification in 3D [11]–[13], we extend the 2D implementation of *Immersions* [4], and visualize NNs as 3D force-directed graphs in VR that allow users to experience the training of the model and manipulate its architecture using virtual hands. We also provide the sonification of the accuracy, loss, learning rate, and momentum for real-time hyperparameter tuning.

# II. RELATED WORK

#### A. Explainable AI and Democratizing AI

The hope of improving AI systems' transparency and accessibility triggered the research of explainable AI [7], [8] and democratization of AI [14]. For example, the AutoAI/AutoML by IBM [15] and H2O.ai [16] automate the end-to-end AI lifecycle to save data scientists from the low-level coding tasks; The TensorFlow Playground [17] and GAN Lab [18] by Google allows direct-manipulation on the in-browser visualizations to help non-experts learn NNs and GANs. Those tools either decrease the experts' workload or help non-experts learn AI, thus requiring numeracy and graph literacy. *Alive* however, focus on making AI training experienceable, thus only relying on basic sensory activities: sight, hearing, and touch in VR, which would potentially reach a broader audience.

### B. Immersive Analytics and Exploration

Immersion provides benefits such as increased spatial understanding, decreased information clutter [9], and the "sense of being there", which is closely associated with satisfaction and appealing experience [10]. VR headsets have been used to provide immersion: *DataHop* enables users to layout data analysis steps in VR [19]; *AeroVR* provides an immersive environment to aid the aerodynamic design [20], and VanHorn et al. developed a deep learning development environment in VR [21]. VR has also been used to teach programming [22]–[24], and students found it more user-friendly, engaging, and better for visualization concepts compared to the traditional web-based system [23]. Thus, we built *Alive* in VR to leverage those benefits.

#### C. Data Visualization and Sonification in 3D

3D data visualization provides the expanded domain of sensibility [11], enabling a more comprehensive understanding of presented information: "data objects", "data sculptures" were built to make data experienceable; Gamelike infographics from datasets were made for playable and engaging experiences [25]. Previous studies have shown that people found 3D visualization to be more satisfied and have lower workloads than the 2D counterpart [26]. Data sonification has been used in various fields such as social sciences [27], [28], arts [29], and health [30], it can enhance visual representations without creating information overload [12], thus suitable for conveying dynamical information [13]. There have been attempts to combine sonification with 3D visualization for representing the connectome of the human brain [13], communicating sensor data in workspaces [31], and assisting music composition [32]. Alive builds upon the node-link visualization [2]-[5] and focuses on sonifying parameters and performances of NNs.

# III. Alive Interface

#### A. Visualization

As shown in Figure 2, the NN is visualized using the node-link approach: (a) Nodes, shown as glowing spheres, represent neurons in the network. Blue nodes represent the first hidden layer; yellow nodes represent the second hidden layer. (b) Links, shown as thin white lines between nodes, represent the weights ( $W_i$ ) between two neurons, with their transparency reflecting the magnitude of the weight: the smaller the weight, the more transparent the link. Limited by the computing power of the VR headset, also for simplicity purposes, we render the input (48 × 48) as a single node in red, the output (seven categories) as a single node in green.

We use a force-directed graph to represent the network. Specifically, the graph floats in a zero-gravity environment, with no energy loss. There are two types of forces between every two nodes (i, j), the attractive  $(FA_{ij})$  and repulsive  $(FR_{ij})$  force. The forces are defined as follows, where  $k_a$  and  $k_r$  being adjustable coefficients and  $W_{ij}$  being the real-time weight between i and j:

$$\overrightarrow{\mathrm{FA}}_{ij} = k_a \times \overrightarrow{W}_{ij}$$
  $\overrightarrow{\mathrm{FR}}_{ij} = \frac{k_r}{\mathrm{distance}^2(i,j)}$ 

For node pairs (i, j) in the same layer, there is no link and weight between them; thus, we use uniform weights with  $|W_{ij}| = 1$  to calculate their attraction. We normalized the value of weights  $(W_{ij})$  to mitigate the impact when weights vary dramatically among neurons.

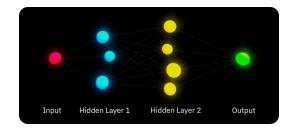


Figure 2. The visualization of the neural network with three neurons in the first hidden layer (blue) and four neurons in the second hidden layer (yellow). The red node and the green node are input and output, respectively.

#### B. Sonification

Finding suitable mappings between the space of data and the space of sounds is conceptual [32]. For simplicity, we map the values of validation *Accuracy* and *Loss* in each epoch directly to the frequency of sine wave oscillators, using a Unity plug-in *Chunity* [33]. Our system plays the sonification of *Accuracy* on both channels by default, but the user can choose to listen to both *Accuracy* and *Loss* at the same time (with *Accuracy* on the right channel, *Loss* on the left), or only the sound of *Loss* on both channels.

#### C. Interaction

*Alive* supports three types of interactions to update the model's number of neurons, learning rate & momentum, and weights of a single neuron (Figure 3).

1) Number of Neurons: To update the number of neurons, the user can move the left hand close to the graph's center of mass (< 5-unit distance in Unity), which would trigger the appearance of a small sphere, indicating the graph is paused. A "Paused" message will be sent to the backend to stop the training. After that, the user can use the right hand to approach one of the hidden layers. Once the right hand enters the threshold of 3-unit distance, a small sphere in the respective layer's color would appear at its center, highlighting that the layer will be manipulated. If the user moves the right hand further closer to the layer's center of mass (< 1-unit distance), a new node will be generated, and the user can drag it to the desired position. To delete a node, the user can drag it back to its layer's center. Once they have done updating, the user can put the left hand down, and the training would restart with the updated number of neurons.

2) Learning Rate and Momentum: Once the training begins, the user can adjust the learning rate by placing the right hand in the mid-air and the left hand close to the left ear. A white sphere would then appear at the network's center, indicating the training is paused. The user can then adjust the magnitude of learning rates by lifting (increasing) or dropping (decreasing) the right hand. The new learning rate's real-time value will be sonified in the same way as *Accuracy* and *Loss* described in Section III-B. Likewise, the user can adjust the momentum by placing the right hand. Once

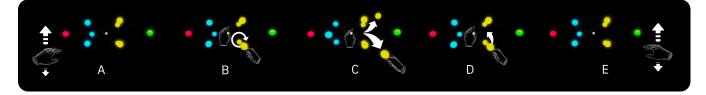


Figure 3. Tuning momentum and learning rate (A, E) through hand movements; Exploring different weights by dragging nodes around (B); Updating the number of neurons by pulling new nodes out of the center (C) or dumping old nodes into the center (D).

the user finishes updating and puts both hands down, the training would resume with updated hyperparameters.

3) Weights of a Single Neuron: We also investigate the idea of updating weights of neurons manually, as opposed to using gradient descent. Similar to the way of updating the number of neurons in Section III-C1, the user can pause the training with the left hand, then drag any existing node in the graph with the right hand. Since the operation would change the distances between the dragged node and the nodes that it connects with, the weights associated with those nodes will be updated and sent to the backend for evaluation. To guide the user on selecting the desired position, the real-time sonifications of Accuracy and Loss are provided, the user can move the node around and find the sweet spot where the pitch of Accuracy sounds high (or low, in the case of Loss) and release the node. After the user puts down the left hand, the training would resume with the updated weights.

#### **IV. IMPLEMENTATION**

## A. Apparatus

The NN model (back-end) runs in the python terminal of a laptop, the 3D visualization and sonification (front-end) was built as a Unity [34] project into the Oculus Quest VR headset [35]. The communication between them was accomplished through TCP connections [36] wirelessly.

#### B. Model

We deployed our system on a simple fully-connected NN in python, based on an intro to machine learning course's materials [37]. The dataset provided to the model is a subset of the Toronto Faces Dataset (TFD) [38], with 3374, 419, and 385 grayscale images from TFD as the training, validation, and testing set, respectively. The network has two hidden layers, each with an adjustable number of neurons. The structure of the network, as well as cross-entropy loss ( $\mathcal{L}$ ), are shown as follows, where  $\mathbf{t}, \mathbf{y}, \mathbf{h}_1, \mathbf{h}_2, \mathbf{x}$  represents the targets, outputs, the first hidden layer, the second hidden layer, and inputs, respectively:

$$\begin{aligned} \mathbf{z}_1 &= \mathbf{W}_1 \mathbf{x} + \mathbf{b}_1 & \mathbf{h}_1 = \text{ReLU}(\mathbf{z}_1) \\ \mathbf{z}_2 &= \mathbf{W}_2 \mathbf{h}_1 + \mathbf{b}_2 & \mathbf{h}_2 = \text{ReLU}(\mathbf{z}_2) \\ \mathbf{z}_3 &= \mathbf{W}_3 \mathbf{h}_2 + \mathbf{b}_3 & \mathbf{y} = \text{Softmax}(\mathbf{z}_3) \\ \mathcal{L} &= -\mathbf{t}^\intercal(\log \mathbf{y}) \end{aligned}$$

In each training step (*i*), weights ( $W_i$ ) are updated according to the Stochastic Gradient Descent (SGD) [39], [40] on the cross-entropy loss ( $\mathcal{L}$ ) with adjustable batch size, momentum ( $\mu$ ) and learning rate ( $\varepsilon$ ), where  $\frac{\partial \mathcal{L}'}{\partial W'_i}$  represent the gradient from the previous step,  $\frac{\partial \mathcal{L}}{\partial W_i}$  represents the current gradient:

$$W_i \leftarrow W_i + \mu \frac{\partial \mathcal{L}'}{\partial W_i'} - \varepsilon \frac{\partial \mathcal{L}}{\partial W_i}$$

After each epoch (input\_size/batch\_size steps), the *Accuracy* and *Loss* of the model's performance on validation sets are calculated and sent back to the VR headset, together with the new weights  $(W_i)$  among all neurons.

#### V. DISCUSSION AND FUTURE WORK

Our preliminary implementation and exploration with *Alive* point out several promising future directions: (1) *Alive* may potentially help users learn and understand neural networks' training concepts. Therefore, we plan to improve the system and conduct comprehensive studies to evaluate its educational benefits; (2) Our system only supports simple neural networks due to the limited computing power of VR systems. Modern deep learning models typically consist of tens or hundreds of thousands of neurons [41], it would be interesting to investigate suitable designs for users to interact with a larger number of neurons in VR environments; (3) Since prior work has found different sounds could evoke different emotional states of the listener [42], it is interesting to explore how different sonification in terms of timbres, pitches, and complexity would affect the user experience.

#### VI. CONCLUSION

This paper presents *Alive*, an interactive representation that brings AI "alive", it leverages visual and auditory feedback to provide an artistic and intuitive way to interact with AI. Since the system does not rely on numerical values or scientific graphs, it could potentially reach a broad audience. While *Alive* is still an early implementation, we hope to share the core idea of representing AI through the combination of 3D visualizations, sonification, and direct manipulation in VR to the broader community. We look forward to stimulating interesting conversations and to eliciting useful feedback for our future development on *Alive*.

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