ELEC576 Final Project Proposal
Neural Vision:
Real-Time Visuals of Neural Network Dynamics

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Abstract

In the rapidly evolving field of Artificial Intelligence, neural networks play a pivotal role yet often operate as enigmatic 'black boxes'. This project proposal outlines a pioneering approach to demystify these complexities through a real-time monitoring interface that visualizes gradient flow and neuron activation during neural network training. Leveraging the MNIST Dataset, our team aims to develop a Fully Connected Neural Network (FCNN) and integrate a visualization system based on the NNSVG structure for dynamic, interactive insights into neural network operations. Our interface will display neurons and connections in varying intensities and colors to represent gradient values and activation levels, offering a neuron-centric view of the training process. This visualization is intended to enhance research capabilities and serve as an educational tool, providing a deeper understanding of neural network functionalities.

In terms of implementation, we plan to develop a back-end system for efficient data management and a web UI for real-time visualizations. The project confronts challenges like data handling, UI development, and algorithm optimization with strategies such as dividing tasks, regular team meetings, and leveraging existing tools to address them. However, scalability to image generation and long-term maintenance remain areas for further investigation. Our proposed system promises significant impacts in neural network research and applications. Enabling the visualization of neuron sparsity could lead to more efficient network designs, aid in transfer learning, and contribute to developing robust AI systems.

This project, while ambitious, is approached with a keen awareness of its feasibility and limitations, embodying a strategic plan to manage these aspects proactively.

Background & Motivation

The rapid evolution of Artificial Intelligence (AI), primarily driven by advancements in neural networks, has been exemplified by transformative technologies like ChatGPT. Despite these strides, neural networks largely remain enigmatic' black boxes' to many researchers. The prevailing approach to neural network research is often trial-and-error, where researchers train models and evaluate performance without a deep understanding of the underlying training dynamics. A fundamental comprehension of neural networks begins with exploring fundamental questions: What roles do neurons play during training? How do gradients propagate through the network? Answering these questions necessitates the development of visualization tools. Pioneers like Zeiler et al. [3] have made strides in CNN visualization, and tools like Net2Vis [1] offer architectural visualizations for Keras-based convolutional networks. However, these tools primarily focus on static architectural representations and do not provide a real-time monitoring interface to observe training dynamics.

Our proposal addresses the current limitations in neural network research by developing an innovative real-time monitoring interface. This interface will provide a comprehensive visualization of both gradient flow and neuron activation during the training of neural networks. It will feature a detailed, neuron-centric perspective, as illustrated in Figure 1, encompassing two distinct visualizations: one for gradient flow and another for neuron activation. For visualizing gradient flow, we will employ a scheme where the brightness of neurons and their linkages corresponds to the magnitude of gradient values. Similarly, for neuron activation, the intensity of a neuron's brightness will indicate its activation level. This dynamic and interactive interface will offer critical insights into the progression of gradient flow and the evolution of neuron activation in real time. Such visualization will significantly enhance researchers' capacity to analyze, diagnose, and comprehend the intricate processes underlying neural network training. In this project, we will specifically focus on fully connected neural networks. This targeted approach will enable us to explore the complex dynamics of neuron activation evolution, sparsity within neurons, and gradient propagation in-depth. Our tool aims to be both practical for immediate research applications and educational, aiding researchers in demystifying the intricate inner workings of neural networks and fostering a deeper understanding of their functionalities.

Implementation & Experimentation

Our project aims to leverage the MNIST Dataset to train a basic Fully Connected Neural Network (FCNN) for classification purposes first. We will then develop features for real-time monitoring of neuron activations and all neuron and parameter gradients, which should be universal and consistent among various neural network architectures. We intend to develop a back-end system using Django to manage data storage efficiently. This system will capture and store data generated during the training phase, including detailed parameter and statistical analyses for each node. This data will be transferred from the back end to a web browser for visualization.

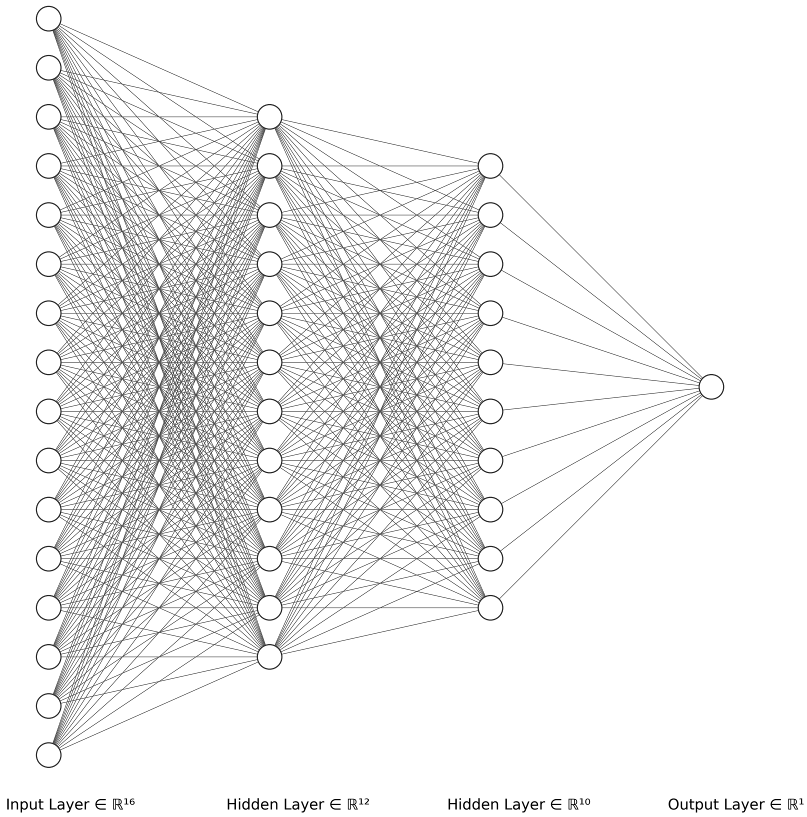

Figure 1: NNSVG Visualization

For the visualization aspect of our project, we have chosen to use the NNSVG structure (Figure 1), initially proposed by Alexander LeNail [2], as our model. NNSVG is adept at providing Scalable Vector Graphics for various Neural Network architectures. Our project will offer static visualization and integrate the back end with a web UI to facilitate real-time network monitoring. In our visualization, each neuron will be depicted as a tiny dot interconnected with other neurons through lines, symbolizing the pathways for parameter transmission. We plan to convey maximum information using various visual elements, such as line thickness and color.

Additionally, we intend to carry out a series of experiments to enhance and refine our visualization system. Our evaluation criteria will encompass several key factors: the system's responsiveness, the accuracy of the visualizations produced, and the efficiency of the monitoring process. Furthermore, we recognize the importance of usability in our system. To ensure a user-friendly experience, we will integrate user feedback into our evaluation process through surveys and practical experiments. These experiments aim to develop a high-performance visualization system capable of effectively handling Neural Networks of various sizes and complexities.

The specific division of labor is as follows:

- Project Leader: Carlos Gonzalez Rivera
- Backend System Development
  - Algorithm: Dominique Dulièpre
  - Backend Framework: Junhao Ran
- Web UI Development: Yifan Wu

Feasibility & Limitations

Our project, aimed at developing a Multi-Layer Perceptron (MLP) using the MNIST dataset for real-time visualization of weights and activations, is a foundational step toward advanced neural network applications. The goal to extend our project to image generation, while ambitious, will remain beyond the scope of this endeavor due to the current timeline and resource constraints. In addressing feasibility, key concerns include:

- **Time Constraints**: A four-member team's tight schedule of less than a month necessitates carefully managing project complexity to fit within this timeframe.
- **Resource Availability**: Ensuring access to adequate computational resources is critical for training and visualizing the MLP.
- **Skillset Distribution**: The project's success relies on our team's ability to effectively cover essential roles, including algorithm development, front-end, and back-end, within our combined skillsets.

We anticipate challenges such as efficient data handling of the MNIST dataset, developing a user interface for real-time visualization, and optimizing the MLP for performance. Our initial solutions addressing these difficulties include:

- **Time Management**: Dividing the project into smaller tasks with clear deadlines.
- **Regular Team Meetings**: Ensuring continuous comms to tackle challenges promptly.
- **Leveraging Existing Tools**: Utilizing existing libraries and frameworks to expedite development.

Unresolved limitations and areas for further investigation encompass the scalability of our MLP model for image generation, understanding long-term maintenance requirements, and exploring advanced neural network visualization and optimization techniques. Our investigative steps moving forward will involve consultations with experts in related fields, a comprehensive literature review on neural network visualization technologies, and early prototype testing to identify technical hurdles and improvement areas. In summary, while ambitious, our project is approached with a realistic understanding of its constraints and challenges. We aim to tackle these proactively, with a strategic plan for managing feasibility concerns and addressing potential challenges and limitations.

Potential Impacts

With the advent of Neural Networks in contemporary applications, the question; "how" is often raised at the marvel of its performance. If a picture is worth a thousand words, then real-time neuron sparsity depiction is a far superior presentation of a neural network and its behavior at each layer. Visualization of the neuron activations and gradient flow aims to help initialize the weights, identify and troubleshoot phenomenons such as vanishing and exploding gradients. Visualizing the neuronal activity through an interface can also help deduce redundancies and inefficiencies in the network, leading to more streamlined and efficient network designs. Visualizing the neuron sparsity will help identify which neurons are active for specific input characteristics and reduce the number of neurons in regions of low activity, making the model more efficient, especially for resource-constrained environments. Visualization can also aid transfer learning by distinguishing the network's generic and task-specific parts. Visualizing neuron sparsity aims to provide more understanding of neural network behavior to foster more efficient, robust, and trustworthy AI systems in Aerospace, Healthcare and other applications of ultimate consequences.

References

[1] Alex Bäuerle, Christian Van Onzenoodt, and Timo Ropinski. Net2vis–a visual grammar for automatically generating publication-tailored cnn architecture visualizations. *IEEE transactions on visualization and computer graphics*, 27(6):2980–2991, 2021.

[2] Alexander LeNail. Nn-svg: Publication-ready neural network architecture schematics. *Journal of Open Source Software*, 4(33):747, 2019.

[3] Matthew D. Zeiler and Rob Fergus. Visualizing and understanding convolutional networks. *CoRR*, abs/1311.2901, 2013.