

Analyzing Neural Network Input Spaces through Network Inversion

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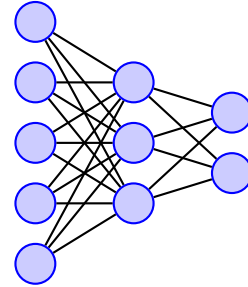
Abstract

Neural networks are often criticized for their lack of interpretability, earning the nickname "black boxes." This lack of transparency poses significant challenges in practical contexts such as AI safety, where understanding how a model arrives at decisions is crucial for preventing harmful outcomes, and debugging, where identifying the source of errors is essential. This paper introduces a framework for systematically inverting neural networks to reconstruct the input space corresponding to a given output. By leveraging linear algebra and function analysis, this approach identifies and explores the free variables introduced due to differences in layer sizes. These free variables provide insights into the degrees of freedom within the network, enabling a deeper understanding of its behavior and flexibility in generating outputs. Through backward propagation and sampling, the methodology reveals the multidimensional input manifolds associated with specific outputs, offering insights into network behavior, decision boundaries, and potential biases. Initial implementations on small-scale networks validate the feasibility of this approach, with ongoing work focused on scaling to larger architectures.

1 Introduction

Neural networks have achieved remarkable success in various domains, from image recognition to natural language processing. However, their "black box" nature limits interpretability, posing challenges for safety, debugging, and trust. Understanding the input-output relationships of a network is crucial for addressing these challenges. This paper presents a method for reconstructing the input space associated with specific outputs, offering insights into the network's internal mechanics.

tivation functions. The diagram below illustrates a simple feedforward network:



2 Methodology

2.1 Neural Network Inversion

Neural network inversion aims to determine the input space corresponding to a given output by propagating backward through the network. The process involves identifying and managing the free variables resulting from layer size mismatches and solving the resulting systems of equations.

2.1.1 Forward and Inverse Propagation

Forward Propagation Equations:

$$wx + b = z, \quad \sigma(z) = a$$

Forward propagation calculates the output of each layer based on the input, weights, biases, and ac-

Inverse Propagation Equations:

$$\sigma^{-1}(a) = z, \quad w^{-1} \cdot z - b = x$$

Inverse propagation reverses the transformations applied during forward propagation. For each layer, the activation function is inverted, and the weights and biases are used to reconstruct the inputs. Free variables emerge when layer sizes differ, as not all inputs can be uniquely determined by the output. These free variables provide a measure of the network's flexibility, indicating how it balances constraints across layers to produce outputs.

3 Analysis of Free Variables

3.1 Matrix Representation and Free Variables

Consider a simple case with 3 input neurons feeding into 2 hidden neurons:

$$\begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}$$

Here, the mismatch in layer sizes introduces one free variable, which must be sampled during inversion. For example, sampling 100 values for the free variable allows us to explore the full input space associated with the output $\begin{bmatrix} z_1 \\ z_2 \end{bmatrix}$. The sampled values reveal how the network resolves degrees of freedom at each layer.

3.2 Simplifying the Linear System

To reduce the system, eliminate variables systematically. Start with:

$$\begin{bmatrix} w_{11} & w_{12} & w_{13} & z_1 \\ w_{21} & w_{22} & w_{23} & z_2 \end{bmatrix}$$

Eliminate the first column in the second row:

$$R_2 - \frac{w_{21}}{w_{11}}R_1 \Rightarrow R_2, \quad \frac{w_{21}}{w_{11}} = k$$

The reduced matrix becomes:

$$\begin{bmatrix} w_{11} & w_{12} & w_{13} & z_1 \\ 0 & w_{22} - kw_{12} & w_{23} - kw_{13} & z_2 - kz_1 \end{bmatrix}$$

From here, we can derive equations for x_1 and x_2 by treating x_3 as a free variable.

3.3 Iterative Sampling of Free Variables

To interpret neural networks effectively, exploring the input space corresponding to a given output is crucial. Free variables are systematically sampled to reconstruct these spaces. The process involves:

1. Identifying free variables layer by layer.
2. Sampling values for free variables (e.g., 100 samples per variable).
3. Propagating backward using inverse transformations.
4. Visualizing the reconstructed input space as a multidimensional manifold.

Neurons that exhibit less variability in achieving specific outputs are inferred to have a higher importance for creating that output. This provides insights into the relative significance of different neurons in the network.

3.3.1 Computational Challenges

Inverse propagation introduces several computational challenges:

Non-uniqueness of Solutions: Layer size mismatches introduce free variables, allowing multiple input configurations to yield the same output. Systematically sampling these variables becomes computationally intensive, particularly for deep networks.

Non-linear Activation Functions: The inversion of non-linear activation functions (e.g., sigmoid, ReLU) can lead to numerical instability, especially when outputs are near the limits of these functions.

Matrix Inversions: High-dimensional weight matrices require substantial computational resources, both in terms of time and memory, to perform inversions.

Error Propagation: Errors introduced at one layer can amplify as the inversion propagates through subsequent layers, leading to inaccuracies in reconstructed inputs.

4 Applications

This framework has the following applications:

- **Model Interpretation:** Understanding input-output relationships.
- **Debugging:** Identifying sensitivities and biases.
- **Generative Insights:** Exploring novel input configurations.

5 Conclusion

This paper presents a novel framework for neural network interpretability through input space reconstruction. By systematically inverting neural networks and analyzing free variables, the approach provides valuable insights into network behavior, decision boundaries, and neuron importance. Future work will focus on scaling this methodology to larger networks and exploring its potential applications in AI safety and generative modeling.

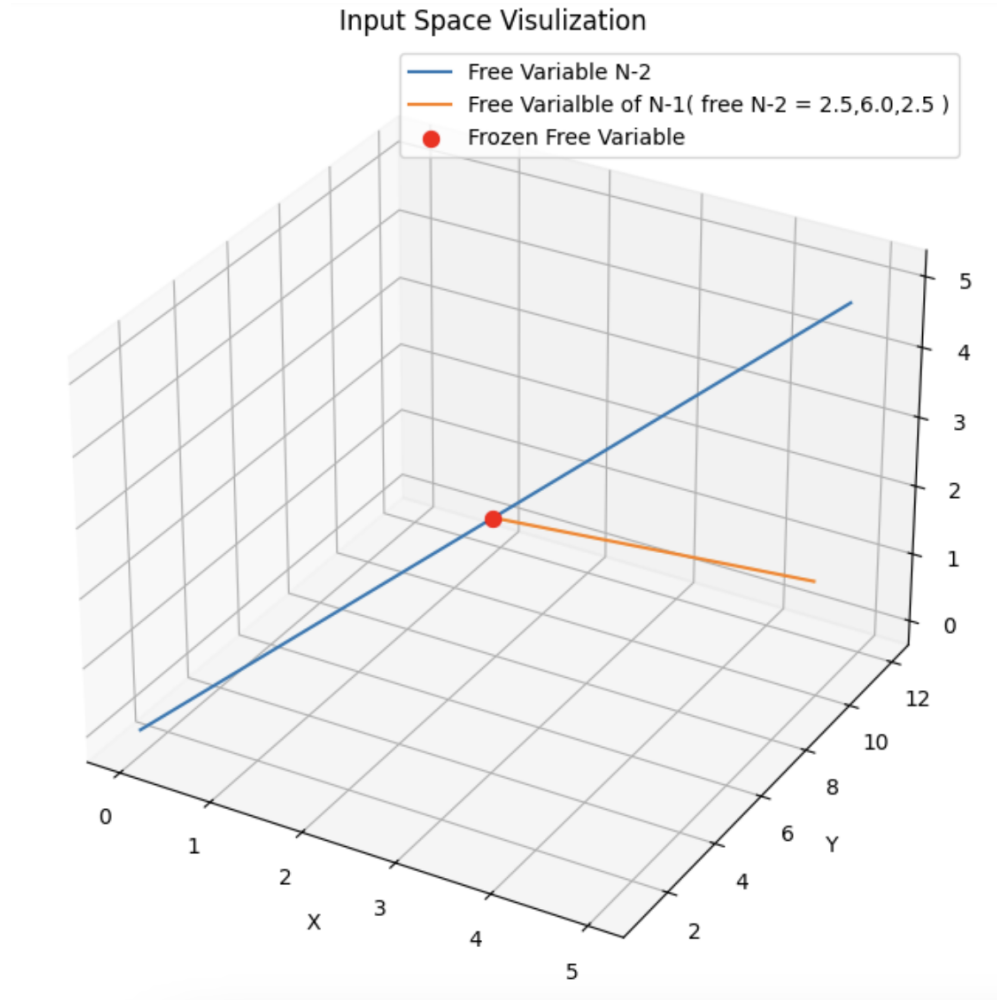


Figure 1: Example of input space reconstruction holding $N - 2$ free variables constant. The manifold shows the variety of valid input configurations for a specific output. For instance, when a network output aligns with $[0.8, 0.2]$, this visualization highlights the range of inputs (e.g., specific features or conditions) that lead to this outcome.