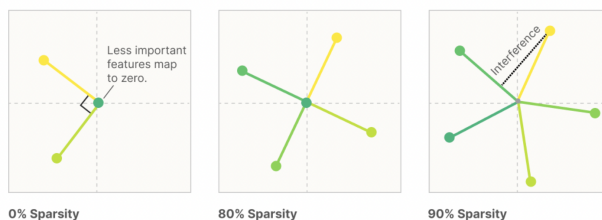

Toy Models of Superposition Replication and Findings

Abstract

Toy Models of Superposition[1] is a groundbreaking paper published by researchers affiliated with Anthropic and Harvard University in 2022. By investigating small models with under 100 neurons, the paper demonstrates that neural networks can represent more features than they have demensions. Additionally, they use these so called “toy models” to understand the relationship between how neural networks are trained and how they represent the data internally. The original paper is quite extensive. As a result, this replication focuses on reproducing the most important results from the introduction and sections 2 and 3 of the original paper. It also includes some comentary on section 1. This document may be expanded to include more examples or other sections in the future.

1 Introduction

The original paper motivates the idea of superposition with the following graphic:



The basic idea is this: if you think of each feature as being represented inside of a neural network by a direction, you can graph these directions and observe them. By doing this, the authors of the original paper demonstrate that the way a model maps features as directions depends on the sparsity of it's training data. A replication of this phenomenon can be found below and the code used to generate it can be found [here](#).

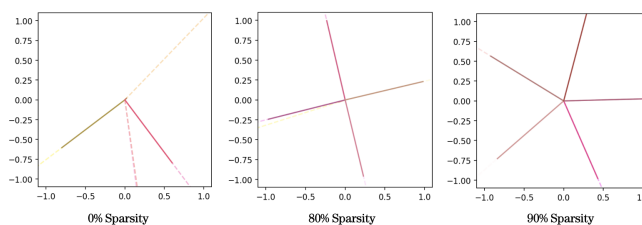


Figure 1: Graphing superposition in 2D.

The model studied in Figure 1 is designed such that each column in the weight matrix corresponds to a given input. Becasuse the weight matrix only represents 2 neurons, the columns of the

matrix can be graphed in 2D. As a result, it is trivial to plot the columns as 2D vectors (each representing individual features of the input). Observing these vectors while increasing the sparsity of the model’s input reveals that the model can be trained to represent many more features than it has dimensions (despite having only 2 neurons, the model in Figure 1 can represent up to 5 features!). This is what the authors call ”superposition.” In future sections we will study superposition extensively and produce the phenomenon in larger networks.

2 Background and Motivation

In this section of Toy Models of Superposition[1], the authors provide context and define terms. In this paper, I make a few additional comments about some of the key ideas from this section.

(1) Defining Features: The original paper Toy Models of Superposition defines features broadly as “properties of the input which a sufficiently large neural network will reliably dedicate a neuron to representing.” The authors do however describe this definition as “slightly circular” and note that they are not “overly attached to it.” I find the definition especially problematic because a network that is small or has unconventional architecture may represent a feature that a larger network or a network with a more typical architecture may represent. These representations are clearly still features, but are not treated as so under the original definition.

As a result, I propose an alternative definition: features are aspects of the input that a neural network represents accurately with a significantly higher probability than a randomly initialized network. In other words, features are parts of the input that a model determines to be important enough to represent internally.

(2) Role of linear Representations in Neural Networks: The original authors of the paper study interpretability by trying to understand the linear representations within neural networks. It is worth noting that this isn’t the only way to approach mechanistic interpretability research. Understanding the role of non-linearities at each level is likely also very important (and perhaps more neglected).

(3) Defining Superposition: The original paper has a compelling yet simple definition for Superposition: “Roughly, the idea of superposition is that neural networks ‘want to represent more features than they have neurons’, so they exploit a property of high-dimensional spaces to simulate a model with many more neurons.” This is the definition I will use throughout this paper.

3 Demonstrating Superposition

In the introduction, the authors of the original paper proved that models with two neurons could exhibit superposition (this result was reproduced in Figure 2). In this section, however, the authors demonstrate that superposition is also observable in models with more than two neurons.

Specifically, they begin by exploring models with 20 inputs and 5 neurons, ultimately proving that these models exhibit superposition under certain conditions. The authors demonstrate this by graphing $W^T W$ for the weight matrix W in each model (shown in Figure 2). They represent positive numbers in the matrix as red and negative ones as blue. They also graph the length of each feature by treating each column in W as a vector. Features that are orthogonal to others in W are labeled black while features that aren’t are labeled yellow (the exact details for how this is calculated is discussed in 3.1).

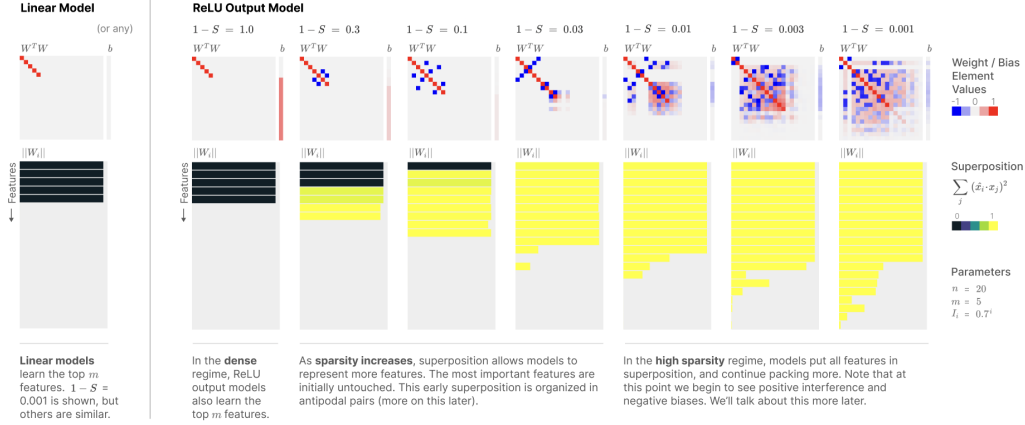


Figure 2: Graphs linear and ReLU models from Toy Models of Superposition [1]

In Figure 2, the authors study both a linear model and a model with a ReLU activation function. They found that both the linear and ReLU model did not exhibit superposition in the absence of sparsity. By increasing the sparsity of the input, however, the ReLU model begins to clearly exhibit superposition by ceasing to represent features orthogonally.

The first step in replicating these findings was to train the linear and ReLU models that don't perform computation in superposition. The linear model was defined by $W^T W x + b$ and the ReLU model was defined by $\text{ReLU}(W^T W x + b)$. I trained both models with Adam (learning rate = $1 * 10^{-3}$) on 20,000 batches of 256 examples.

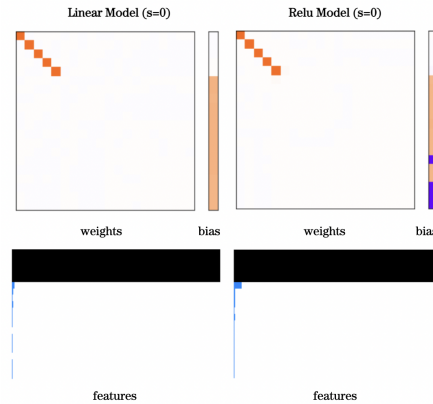


Figure 3: The generated graphics show that the model uses each of its five dimensions to graph the 5 most important features orthogonally.

Note that in Figure 3, I use orange to indicate positive numbers and purple to indicate negative ones. This is different from the red and blue in Figure 2, to distinguish my work from that of the original authors. Similarly, while the original authors use yellow to indicate features in superposition, I use blue (This is hard to see in Figure 3 but it will be more obvious going forward).

3.1 Calculating Superposition

The models in Figure 3 do not exhibit superposition. They encode each five most important features orthogonally (one feature for each neuron in the model). Going forward however, we will be investigating models that do not behave that way, instead encoding features as vectors that interfere with each other. In order to explain this phenomenon, and describe the graphs in Figure 4 it will be useful to dive a little bit into some math. The color of the feature bars at the bottom of Figure 4 are determined by the following equation.

$$\text{Interference} = \sum_{j \neq i} (\hat{W}_i \cdot \hat{W}_j)^2 \quad (1)$$

For a given column i in weight matrix W , it calculates interference by taking the dot product with every other column in W . Non-zero dot products indicate that the columns in W are not orthogonal. As a result, summing these dot products gives a general idea of how much the network is representing a given feature in superposition. Note that \hat{W}_i is the unit vector for W_i . This is necessary because when calculating interference, we are interested in the direction of a given feature, not its length.

In Figure 4 the length of a feature (calculated by taking the length of the vector W_i) determines the lengths of the bars in the feature graph. The interference equation (Equation 1) determines the color of the columns: black indicates a low value for Equation 1 while blue indicates a higher value. Blue bars show that a given feature is represented in superposition while black bars indicate that the feature is mapped orthogonally.

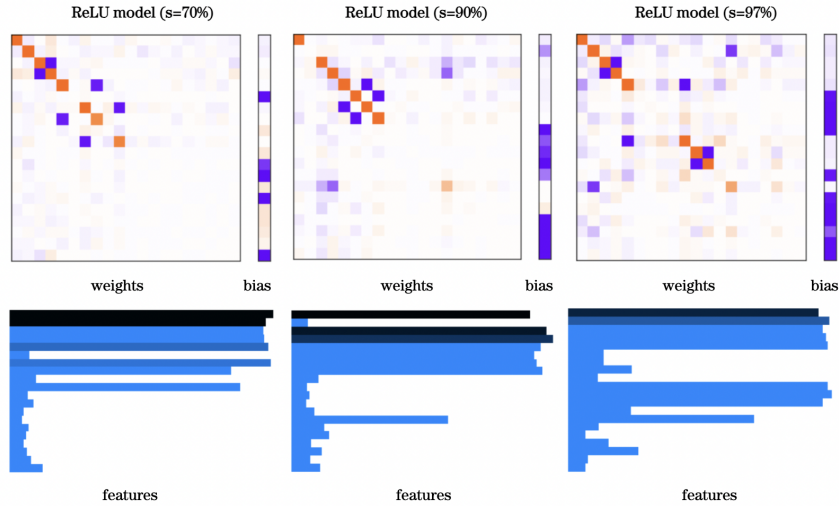


Figure 4: By varying sparsity, superposition observed in ReLU models. This figure shows three models with increasing sparsity levels. As sparsity is increased, more features are mapped in superposition.

References

- [1] Nelson Elhage, Tristan Hume, Catherine Olsson, Nicholas Schiefer, Tom Henighan, Shauna Kravec, Zac Hatfield-Dodds, Robert Lasenby, Dawn Drain, Carol Chen, Roger Grosse, Sam

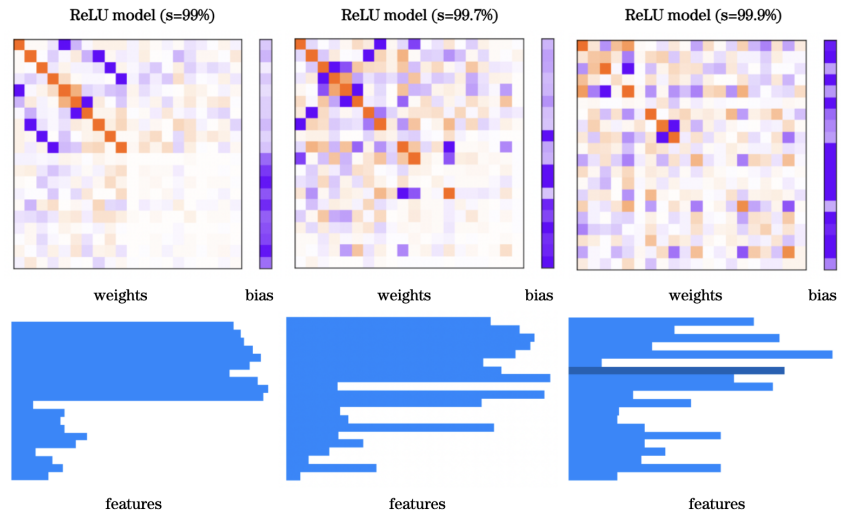


Figure 5: By increasing sparsity even more, the model represents even more features in superposition.

McCandlish, Jared Kaplan, Dario Amodei, Martin Wattenberg, and Christopher Olah. Toy models of superposition, 2022.