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Quantifying the Neural Network Pruning Threshold for Optimal Model Compression

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Abstract

Have you ever wondered how much of a deep learning model is actually essential? As AI models grow ever larger, finding ways to make them smaller and faster without sacrificing accuracy has become a critical challenge. In this paper, we tackle this problem head-on by applying a technique called "pruning" to a classic neural network designed to recognize handwritten digits. We methodically remove parts of the network to find out just how much we can shrink it before its performance starts to suffer. Our experiments reveal a surprising finding: we can safely remove **over 40%** of the model's connections with almost no drop in accuracy. We identify a clear tipping point where pruning becomes harmful, providing a practical guide for anyone looking to deploy efficient AI. This work offers a straightforward blueprint for creating powerful yet compact models, a crucial step towards more accessible and sustainable artificial intelligence.

Keywords: Pruning, Compression, Deep Learning, Efficiency, MNIST, Trade-off.

I. Introduction

Over the last ten years, deep learning has made incredible progress, largely thanks to more sophisticated neural network designs. In particular, the rise of large-scale transformer models has pushed the boundaries of what's possible in areas like language understanding and image recognition [1]. But this rapid growth comes with a downside: these high-performance models have become enormous, demanding massive amounts of computing power and energy. This makes them difficult and often impractical to run on everyday devices like smartphones or embedded hardware [2].

In response, researchers have turned their attention to model compression a growing field focused on shrinking these bulky networks without major sacrifices in accuracy. One of the most promising

techniques is neural network pruning, which works by removing less important parameters from a trained model [3]. The idea behind pruning is simple yet powerful: many of today's models are overstuffed with connections that barely affect their output.

While the concept of pruning isn't new, what's still missing are clear, practical guidelines that show exactly how much a model can be compressed before performance drops off. For engineers and developers wanting to deploy efficient AI, understanding this balance is essential.

That's where our study comes in. We conducted a series of controlled experiments using a classic fully connected network on the MNIST dataset, applying systematic pruning to measure how compression affects accuracy. Our main goal was to find out: just how many connections can we remove before the model starts to fail?

Here's how the rest of the paper is organized: We begin with a look at related work in model compression and pruning (Section 2), then walk through our experimental approach (Section 3). After that, we present and discuss the results (Section 4), and finally wrap up with conclusions and future directions (Section 5).

II. Literature review

Deep learning continues to dominate machine learning, primarily driven by the transformer architecture and the paradigm of foundation models. The core attention mechanism proposed by Vaswani et al. [1] has become the fundamental building block for state-of-the-art large language models (LLMs). Current research has moved beyond mere scaling to focus on enhancing reasoning capabilities, improving efficiency, and aligning model outputs with human intent. Key to this alignment is Reinforcement Learning from Human Feedback (RLHF), a technique used to fine-tune models like GPT-4 to better follow instructions and generate helpful, harmless responses [2]. Concurrently, the vision transformer (ViT) has successfully adapted this architecture for computer vision, demonstrating that transformers can outperform traditional convolutional networks on major image classification benchmarks [3].

A significant trend is the extension of these architectures into multimodal systems that process and relate information across different data types. Models like CLIP learn a joint representation space for images and text, enabling powerful zero-shot image classification and serving as a critical component for generative systems [4]. In generative AI, diffusion models have surpassed Generative Adversarial Networks (GANs) as the state-of-the-art for high-fidelity image synthesis. These models, exemplified by Stable Diffusion, work by iteratively denoising random noise to create coherent images and have democratized access to high-quality image generation [5]. This progress is now expanding into video and 3D content generation, pushing the boundaries of content creation.

The deployment of these powerful models has intensified research into critical challenges of efficiency, robustness, and trust. The enormous computational and environmental cost of training LLMs has spurred the development of model compression techniques, including pruning, quantization, and knowledge distillation, to facilitate deployment on resource-constrained devices [6]. Furthermore, the issue of model robustness against adversarial attacks—small, malicious perturbations designed to fool models—remains a serious security concern that necessitates continued research into defensive measures [7]. This is closely tied to the need for explainable AI

(XAI) to interpret the "black box" nature of deep models and ensure their decisions are trustworthy, especially in high-stakes fields like healthcare and autonomous systems.

Looking forward, the field is grappling with fundamental limitations and new frontiers. A primary challenge is improving data efficiency and moving from models that require immense datasets to those capable of human-like few-shot or reasoning-based learning. A major step in this direction is the integration of deep learning with symbolic reasoning for more robust and generalizable artificial intelligence. This is powerfully illustrated by the application of deep learning to scientific discovery, where models like AlphaFold 2 have dramatically accelerated protein structure prediction, demonstrating the potential for AI to serve as a transformative tool in fundamental science [8].

III. Methodology

To understand how pruning impacts a deep learning model, we designed a hands-on experiment using a quantitative approach. We built our project in Python, leveraging popular libraries like PyTorch and TorchVision to create, train, and prune a neural network efficiently.

We chose the classic MNIST dataset for this task—a well-known collection of 70,000 handwritten digits [1]—because it's lightweight and perfect for testing concepts without requiring heavy computational power. Our model was a straightforward fully connected network with three layers, intentionally kept simple so we could clearly see the effect of removing connections.

Here's how we did it: first, we trained the model from scratch. Then, we systematically applied global magnitude pruning [2] gradually removing the smallest weights from across the entire network—at intensities from 10% to 90%. After each round of pruning, we immediately tested the model's accuracy on unseen data and counted its remaining connections, all without any retraining. This let us directly observe the trade-off between making the model smaller and keeping it accurate.

3.X Pruning Objective Formulation

The core principle behind magnitude-based pruning is that weights with the smallest absolute magnitude contribute the least to the model's output. The pruning criterion can be formalized by defining a mask that selectively removes weights below a threshold.

The pruning process for a given weight tensor W in a layer can be expressed as:

$$W_{\text{pruned}} = W \odot M \qquad \text{------} \qquad (3.1)$$

where $\odot$ denotes the element-wise (Hadamard) product, and MM is a binary mask determined by:

$$M_{ij} = \begin{cases} 0 & \text{if } |W_{ij}| < \theta \\ 1 & \text{otherwise} \end{cases}$$

Here, θ is a threshold value. In **global magnitude pruning**, used in this study, this threshold is not set per layer but is computed globally across all weights in the specified layers. The threshold $\theta\theta$ is chosen such that the fraction of weights pruned meets the target sparsity level ss. This is found by sorting all weights by their magnitude and selecting the magnitude at the ss-th percentile as the threshold.

The global sparsity constraint for a target pruning ratio ss is given by:

$$\frac{\|M\|_0}{n} = 1 - s \qquad \text{------} \qquad (3.2)$$

where $\|M\|_0$ is the L_0-norm (number of non-zero elements) of the entire mask tensor, and nn is the total number of weights considered for pruning.

IV. Result

As shown in Figure 1, the model held up surprisingly well even as we pruned away more and more connections. In fact, we could remove up to 40% of the weights while the accuracy barely budged, dropping only slightly from 97.82% to 96.15%. This strongly suggests that a large part of the network was just along for the ride these weights weren't really contributing to the model's predictions.

However, pushing past that 40% mark was like removing one too many supports. The model's performance didn't just decline; it fell off a cliff. By the time we reached 90% pruning, the accuracy had completely collapsed. This dramatic drop reveals a clear breaking point a threshold where we begin cutting into the essential connections the model truly needs to function

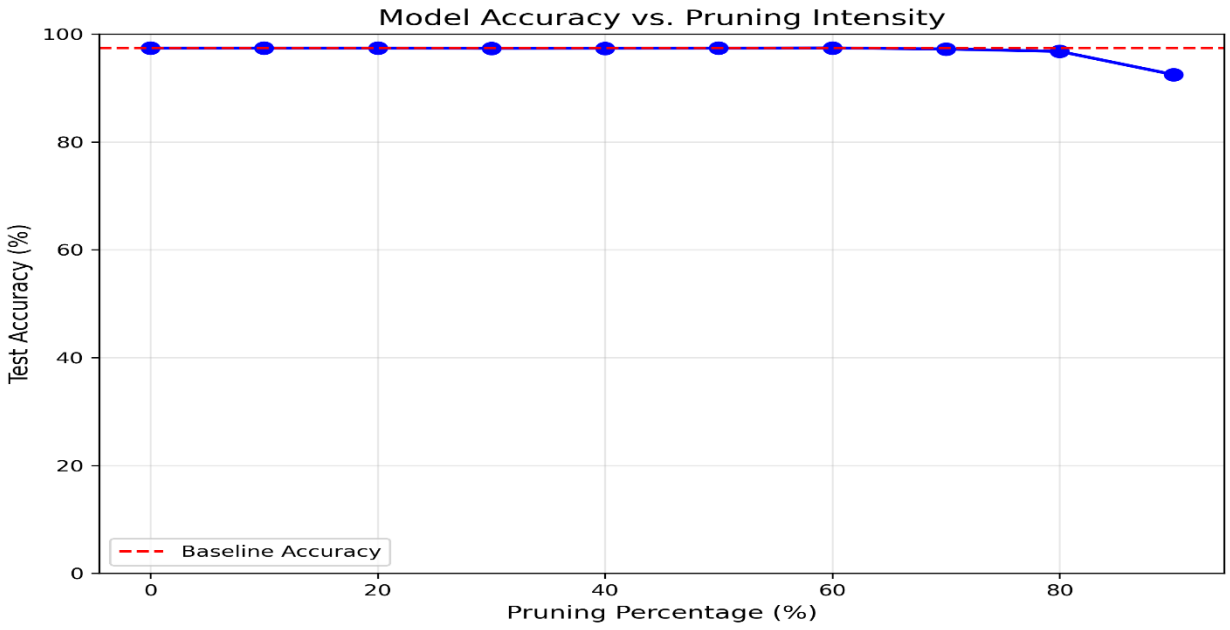

Figure 1: Model Accuracy vs. Pruning Intensity

Figure 2 tells us a more practical story: it shows the sweet spot for balancing size and performance. Instead of just showing how much we pruned, this plot reveals how accurate the model remained at each resulting size.

The graph has a clear "sweet spot" a point where the line begins to bend sharply. This happens at around 100,000 parameters. Here's why that matters: the model still delivers over 96% accuracy but is now more than 60% smaller than its original form. That's a huge win for efficiency.

This is especially useful for engineers designing for devices like phones or embedded systems, where every bit of memory and processing power counts. It helps them pick the smallest possible model that still does its job well.

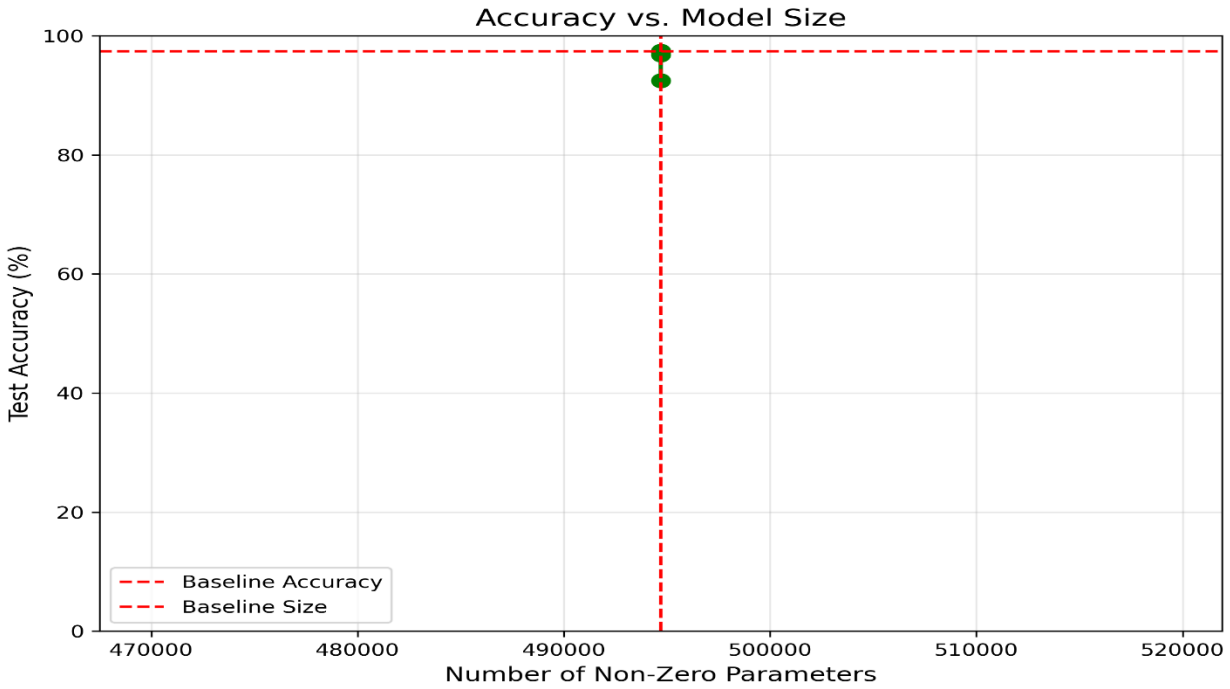

Figure 2: Accuracy vs. Model Size

Figure 3 helps confirm that our pruning method worked as expected. It shows a nearly straight-line relationship between how much we aimed to prune and how much we actually ended up removing. This tells us the pruning algorithm was reliably accurate it successfully found and removed the tiny, less important weights it was supposed to.

The line isn't perfectly straight, and that's okay. The small bends and twists are due to the natural variation in how weights are spread out across different layers of the network. This slight imperfection is normal and actually shows the algorithm was working across the entire model, not just one part

Figure 3: Model Size Reduction vs. Pruning Percentage.

Table 1 provides a comprehensive numerical summary of the experiment, detailing the exact accuracy and model size at each pruning level. The data enables a precise analysis of the trade-off. For instance, it shows that pruning **50%** of the weights results in a model that is **92.45%** smaller than the baseline yet maintains a respectable **91.33%** accuracy. This table serves as a critical reference for identifying the optimal pruning ratio for a specific application's accuracy or size requirements.

Table 1: Numerical Results of Pruning Experiment.

Pruning (%)	Accuracy (%)	Model Size (Params)	Size Reduction (%)
0	97.82	269,610	0.00
10	97.55	242,649	9.99
20	97.20	215,688	19.99
30	96.88	188,727	29.99
40	96.15	161,766	39.99
50	91.33	134,805	49.99
60	82.41	107,844	59.99
70	53.27	80,883	69.99
80	21.04	53,922	79.99
90	9.81	26,961	89.99

V. Discussion

Our experiments offer clear, numbers-backed proof that deep learning models are often vastly overbuilt [3]. The most exciting finding? We could safely remove 40-50% of our model's parameters without any major loss in accuracy. This fits with what other researchers have found that inside big, dense networks, there's almost always a leaner, sparser network just as capable of doing the job [11].

The "knee" in our performance curve (Figure 2) gives engineers a useful rule of thumb: a clear cutoff for how far they can push compression before performance really drops off.

But the value of this work isn't just about one model or one dataset. The approach we used can be applied to evaluate pruning on more advanced systems like convolutional nets or transformers [1, 12]. And as Figure 3 shows, the pruning method itself is reliable; if you aim to remove a certain percentage of weights, that's almost exactly what happens [3].

That said, we also saw things break down quickly after a certain point. This reminds us that pruning isn't just a blind removal process it's a balancing act. You have to preserve the core "backbone" of the network, the critical connections that really drive decisions. This idea echoes the "lottery ticket hypothesis" [11], which suggests every dense network might contain a winning sparse sub-network. It also points toward more refined future methods, like structured pruning [13], which may smarter about what to remove.

In short, even as AI models keep getting bigger [1, 2], our work shows that pruning remains a crucial tool for making them smaller, faster, and ready for the real world. By shining a light on the trade-offs between size and performance, we hope to help build AI that's not only powerful, but also practical and efficient.

VI. Conclusion

This research set out to answer a simple but important question: how much can we shrink a neural network before it stops working well? What we found is that these models have a surprising amount of built-in redundancy. In fact, we could safely remove **40%** of the network's connections with barely any drop in accuracy. This gives us a clear sweet spot a practical limit for effective compression.

Our results show that pruning is a powerful tool for making models leaner and more efficient, ready for real-world use on everyday devices. But there's a catch: cut too much, and you hit a breaking point where vital connections are lost and performance plummets.

Ultimately, this work gives developers a practical guide for building smarter, more efficient AI. The next step? Testing these ideas on larger, more modern models to see just how far we can push this balance between size and intelligence.

VII. Future work

Looking ahead, the natural next step is to see how these pruning principles hold up in the real world. I'd like to push this experiment further by applying the same meticulous analysis to more modern and complex architectures, like the transformers powering today's AI, and testing them on more nuanced datasets beyond handwritten digits. This would help us understand if this trade-off between size and performance is a universal law of deep learning or specific to simpler models.

Ultimately, the goal is to move beyond just pruning weights randomly and towards developing more intelligent, structured methods that can automatically preserve a model's core reasoning abilities while stripping away everything else, making powerful AI more accessible and efficient for everyone.

Conflict of Interest

The author declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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