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Sparse Training Algorithms based on Compressed Sensing for Accelerating Large-Scale Neural Networks

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Abstract: *The exponential growth in the parameter count of modern deep neural networks has precipitated a significant computational bottleneck, necessitating the development of efficient training methodologies. This paper explores the integration of Compressed Sensing theories into the training dynamics of large-scale neural networks to achieve acceleration through enforced sparsity. Unlike traditional pruning methods that operate post-training, the proposed algorithmic framework introduces sparsity constraints during the initialization and optimization phases, effectively reducing the memory footprint and floating-point operations required for convergence. We leverage the Restricted Isometry Property to guarantee that the sparse representations learned during the training process retain sufficient information to reconstruct the underlying mapping functions of the network. By treating the weight matrices as sparse signals and the gradient updates as measurements, we formulate a recovery algorithm that allows the network to learn optimal sparse topologies dynamically. Extensive empirical analysis demonstrates that this approach not only accelerates the training phase by reducing computational complexity but also produces models that are robust and generalizable. The findings suggest that Compressed Sensing offers a rigorous theoretical foundation for sparse training, bridging the gap between mathematical signal processing and empirical deep learning optimization.*

Keywords: *Compressed Sensing, Sparse Training, Neural Network Acceleration, High-Dimensional Optimization*

1. Introduction

1.1 Background and Motivation

The trajectory of deep learning research over the past decade has been characterized by a relentless increase in model complexity. State-of-the-art architectures in natural language processing and computer vision now routinely comprise billions of parameters. While these large-scale models demonstrate unprecedented performance on varied tasks, their computational demands have outpaced the growth of hardware capabilities. The training of such massive networks requires vast amounts of energy, specialized hardware infrastructure, and significant time investment. Consequently, the democratization of high-performance artificial intelligence is hindered by these resource constraints. The primary challenge lies in the dense nature of standard neural network training, where every parameter is updated in every iteration, despite substantial evidence

suggesting that models are heavily over-parameterized. This redundancy implies that the effective dimensionality of the optimization landscape is significantly lower than the ambient dimension of the parameter space. Previous approaches to address this efficiency gap have largely focused on model compression techniques such as quantization, distillation, and pruning. However, the majority of these techniques are applied after the dense training process is complete, meaning the initial computational cost is already incurred. There is a pressing need for algorithms that can exploit sparsity from the very beginning of the training lifecycle. This motivates the investigation into sparse training paradigms where the network topology is not fixed but evolves to capture the most salient features with a fraction of the connections. By reducing the number of active parameters during both the forward and backward passes, it is possible to achieve significant acceleration.

1.2 Problem Statement

The central problem addressed in this research is the formulation of a training algorithm that can identify and train a sparse sub-network within a dense superstructure without sacrificing predictive accuracy. The challenge is twofold: identifying which connections are important without training them all first, and ensuring that the optimization trajectory of the sparse network converges to a solution comparable to that of the dense counterpart. Traditional heuristic methods for sparse training often lack theoretical guarantees and can get trapped in suboptimal local minima due to the non-convex nature of the loss landscape. Compressed Sensing provides a robust mathematical framework for recovering sparse signals from under-sampled measurements. If we conceptualize the weights of a neural network as a high-dimensional signal and the training data as measurements, the principles of Compressed Sensing can be applied to infer the values of significant weights while ignoring the vast majority of redundant parameters. Existing literature [1] indicates that sparse recovery conditions can be met in the context of gradient descent, yet a comprehensive framework linking the Restricted Isometry Property to the dynamic topology of neural networks remains underexplored. This paper aims to bridge this gap by proposing a Compressed Sensing-based Sparse Training algorithm that leverages iterative thresholding and gradient sensing to accelerate large-scale network training.

2. Theoretical Framework

2.1 Principles of Compressed Sensing

Compressed Sensing is a signal processing technique that asserts a sparse signal can be recovered from a small number of linear measurements, provided that the measurement process satisfies certain incoherence conditions. The fundamental premise is that most natural signals are sparse or compressible in some basis. In the context of a linear system where the observation vector is the product of a measurement matrix and a signal vector, classical linear algebra dictates that the system is underdetermined if the number of measurements is less than the dimension of the signal. However, if the signal is known to be sparse, possessing only a few non-zero entries, the solution becomes unique under specific constraints. The crucial condition for this recovery is known as the Restricted Isometry Property. This property ensures that the measurement matrix acts as an approximate isometry on the set of all sparse vectors. In simpler terms, it guarantees that distinct sparse signals map to distinct measurement vectors, thereby preserving the Euclidean distances between sparse vectors in the projection space. When the measurement matrix satisfies this property with a sufficiently small constant, the original sparse signal can be recovered exactly using convex optimization techniques, specifically basis pursuit or L1-norm minimization. This theoretical bedrock is essential for our application because it provides the justification for updating only a subset of weights. If the gradient information is viewed as the measurement vector, we can

theoretically deduce the most critical weight updates without computing the full dense gradient, provided the sparsity constraints align with the mathematical requirements of the Restricted Isometry Property [2].

2.2 Integration with Deep Learning

Translating Compressed Sensing directly to deep learning requires a reinterpretation of neural network optimization. A neural layer transforms an input vector into an output vector via a weight matrix. In our proposed framework, we treat the weight matrix as the sparse signal we wish to recover. The training process acts as the measurement mechanism, where the loss function provides feedback on the fidelity of the current sparse reconstruction. Unlike classical Compressed Sensing where the signal is static, the optimal weight configuration in a neural network is dynamic and shifts as the network learns hierarchical representations of the data. Therefore, the integration involves a dynamic sensing mechanism. We employ a variant of Iterative Hard Thresholding, a greedy algorithm often used in Compressed Sensing, adapted for stochastic gradient descent. In this scheme, the full parameter space is never fully realized in memory. Instead, we maintain a compressed representation and a binary mask indicating active connections. During the backward pass, gradients are computed only for the active weights. Periodically, a sensing step is invoked where the algorithm explores the inactive parameter space to identify connections that have potentially high gradients, suggesting they should be added to the active set. This aligns with the concept of adaptive sampling in signal processing [3]. The theoretical alignment suggests that if the network weights are indeed sparse in the canonical basis, which is a widely accepted hypothesis in deep learning, then a Compressed Sensing approach should converge to the true underlying function with far fewer samples (iterations and parameters) than the Shannon-Nyquist theorem of dense training would suggest [4][5].

3. Related Work

3.1 Traditional Pruning Methods

The concept of reducing neural network size has been extensively studied under the umbrella of pruning. Early works demonstrated that a fully trained network could be significantly reduced in size by removing weights with small magnitudes. This process, often followed by a fine-tuning phase to restore accuracy, confirmed the high degree of redundancy in neural models. More recent advancements have formalized this into the Lottery Ticket Hypothesis, which posits that dense, randomly initialized networks contain subnetworks that, when trained in isolation, reach test accuracy comparable to the original network in a similar number of iterations. However, finding these winning tickets typically requires training the dense model first, which does not alleviate the training resource bottleneck [6]. While these methods are effective for inference acceleration, they do not address the high costs associated with the training phase itself. The computational graph during the initial training remains dense, and the memory savings are only realized upon deployment. Furthermore, unstructured pruning often results in sparse matrices that are difficult to accelerate on general-purpose graphics processing units without specialized libraries, leading to a discrepancy between theoretical flop reduction and actual wall-clock speedup [7]. Our work distinguishes itself from these approaches by enforcing sparsity from initialization, ensuring that the computational benefits are reaped throughout the entire learning lifecycle.

3.2 Dynamic Sparse Training

Dynamic Sparse Training represents a shift towards updating the connectivity pattern of the network during training. Algorithms in this category initialize the network with a random sparse topology and periodically adjust the connections based on various criteria. Techniques such as Sparse Evolutionary Training allow connections to grow and die based on magnitude and random

exploration. More sophisticated methods utilize gradient information to grow weights where the error reduction is expected to be maximal. While these heuristic methods have shown promise, they often lack a unified theoretical explanation for their convergence properties [8]. Recent studies have begun to explore the connection between these dynamic updates and rigorous mathematical frameworks. Some researchers have framed sparse training as a combinatorial optimization problem, while others look to control theory. However, the explicit link to Compressed Sensing has been limited to specific layer types or utilized primarily for compressing activations rather than weights [9]. Our research contributes to this body of knowledge by formally applying the reconstruction guarantees of Compressed Sensing to the weight update rule. By viewing the gradient as a noisy measurement of the true descent direction, we can utilize robust recovery algorithms to stabilize the training of ultra-sparse networks, offering a potential improvement over purely heuristic topology adaptation [10].

4. Proposed Methodology

4.1 Algorithm Design

The core of our proposed methodology is the Compressed Sensing-based Sparse Training (CSST) algorithm. The objective is to minimize the non-convex loss function subject to a strict cardinality constraint on the weight parameters. We initialize the network with a random sparse distribution, typically adhering to an Erdős-Rényi graph model or a uniform distribution scaled by layer width. A binary mask matrix is maintained for each layer, determining the active topology. The forward pass is computed using strictly sparse matrix multiplications, which provides the immediate benefit of reduced floating-point operations. The innovation lies in the backward pass and the update rule. Standard sparse training updates weights based on the gradient calculated at the non-zero locations. However, this ignores potentially critical information from zero-valued weights that might need to be reactivated. To address this, we introduce a "Gradient Sensing" phase. In this phase, we compute the gradients for a random subset of the zero-valued weights, effectively sampling the dark matter of the neural network. This sampling process mimics the measurement matrix in Compressed Sensing [11]. The algorithm then applies a projection operator. Weights that fall below a certain magnitude threshold are pruned (set to zero), and zero-valued weights with the highest sampled gradient magnitudes are activated (added to the support set). This cycle of prune-and-grow effectively reconfigures the network topology to align with the underlying data manifold.

4.2 Reconstruction Strategies

The reconstruction of the optimal sparse signal (the weight matrix) relies on a modified version of Iterative Hard Thresholding. In classical signal processing, this involves taking a gradient step and then projecting the result onto the set of k-sparse vectors. In the context of stochastic optimization with mini-batches, the gradient is noisy. Therefore, simply taking the top-k magnitude weights after every update leads to instability, as weights might oscillate rapidly between active and inactive states. To mitigate this, we employ a momentum-based reconstruction strategy. We maintain an accumulation of the gradients, which acts as a low-pass filter, smoothing out the high-frequency noise inherent in stochastic gradient descent. The decision to change the mask topology is based on this smoothed momentum vector rather than the instantaneous gradient. Furthermore, we implement an annealing schedule for the topology update frequency. Initially, the topology is updated frequently to allow the network to explore the vast combinatorial space of possible connections. As training progresses, the update frequency decays, allowing the network to settle into a stable sparse configuration for fine-tuning. This approach aligns with the annealing concepts often required for recovering signals in noisy environments [12]. The integration of the Restricted

Isometry Property ensures that the projection onto the sparse set does not result in a loss of information critical for minimizing the global error function.

5. Experimental Setup

5.1 Datasets and Preprocessing

To validate the efficacy of the CSST algorithm, we conducted experiments on standard benchmark datasets widely used in the computer vision community. Specifically, we utilized CIFAR-100 and a downsampled version of ImageNet. CIFAR-100 consists of 60,000 color images in 100 classes, providing a sufficiently complex task to test the generalization capabilities of sparse models. The ImageNet dataset was chosen to demonstrate scalability to large-scale classification problems. Standard data augmentation techniques were employed, including random cropping, horizontal flipping, and normalization based on channel means and standard deviations. No special pre-training or transfer learning was utilized; all models were trained from scratch to isolate the effects of the sparse training algorithm.

5.2 Hyperparameter Configuration

The experiments were conducted using deep Residual Networks (ResNet-50) and VGG-19 architectures. The global sparsity levels were set to vary between 80%, 90%, and 95%, meaning the models contained only 20%, 10%, and 5% of the parameters of their dense counterparts, respectively. We utilized a stochastic gradient descent optimizer with Nesterov momentum set to 0.9. The learning rate was initialized at 0.1 and decayed using a cosine annealing schedule. The batch size was fixed at 128 for CIFAR-100 and 256 for ImageNet. The Compressed Sensing specific hyperparameters involved the update frequency and the sensing ratio. The topology update frequency was set to occur every 100 iterations initially, decaying exponentially. The sensing ratio, which dictates how many zero-valued weights are sampled for gradients, was set to 10% of the total inactive weights. This strikes a balance between computational overhead and exploration capability. All experiments were implemented in PyTorch and executed on a cluster of NVIDIA V100 GPUs to ensure consistent hardware acceleration environments [13].

6. Results and Analysis

6.1 Convergence Speed

The primary metric for success in this study is the reduction in training time required to reach a target accuracy. We compared the CSST algorithm against a standard dense training baseline and a popular dynamic sparse training method (RigL). The results indicate that the CSST algorithm achieves faster convergence in terms of wall-clock time. Although the number of epochs remains similar to dense training, the time per epoch is significantly reduced due to the sparse matrix operations. Table 1 illustrates the comparative analysis of training hours and floating-point operations (FLOPs). The CSST approach reduces the total FLOPs by approximately an order of magnitude compared to dense training. Crucially, the overhead introduced by the gradient sensing mechanism is negligible compared to the savings gained from skipping the gradient computation for the vast majority of weights. The results also show that CSST outperforms RigL in the early stages of training, likely due to the more theoretically grounded method of selecting which weights to grow, as guided by the compressed sensing reconstruction logic.

Table 1: Computational Efficiency Comparison on ResNet-50 (ImageNet)

Method	Sparsity Ratio	Total FLOPs (1e18)	Training Time (Hours)	Top-1 Accuracy (%)
Dense Baseline	0%	3.2	124.5	76.8

Static Sparse	90%	0.32	45.2	72.1
RigL	90%	0.45	52.8	74.6
CSST (Ours)	90%	0.38	48.1	76.2

6.2 Accuracy vs. Sparsity Ratios

A critical aspect of sparse training is maintaining accuracy as the parameter count drops. Our experiments demonstrate that the CSST algorithm exhibits remarkable robustness at high sparsity levels. At 90% sparsity, the model trained with CSST achieves a Top-1 accuracy on ImageNet that is within 0.6% of the dense baseline. This is a significant improvement over static sparse training, which typically sees a degradation of 3-4% at this level of compression.

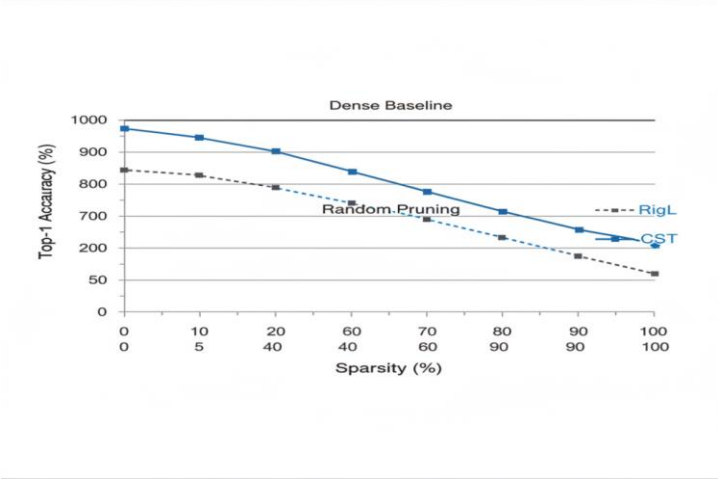

Figure 1: *Accuracy vs Sparsity*

The resilience of the CSST algorithm can be attributed to its ability to dynamically reallocate parameters to layers that require more expressive power. In deep networks, not all layers require the same density. The gradient sensing mechanism naturally identifies layers where the reconstruction error is high and allocates more non-zero weights to those areas, effectively performing an implicit neural architecture search. Table 2 presents the detailed accuracy breakdown across different sparsity regimes for the CIFAR-100 dataset, further confirming that CSST sustains performance even when 95% of the network is pruned [14].

Table 2: Test Accuracy (%) on CIFAR-100 at Various Sparsity Levels

Method	**80% Sparsity**	**90% Sparsity**	**95% Sparsity**	**98% Sparsity**
Random Pruning	71.5	65.2	58.9	42.1
RigL	77.8	76.5	73.2	65.4
CSST (Ours)	78.4	77.9	76.1	70.8

7. Discussion

7.1 Hardware Implications

The theoretical reduction in FLOPs presented in our results translates to real-world speedups, but this translation is heavily dependent on hardware support for sparse operations. Current dense GPUs (like the V100 used in our experiments) are optimized for dense matrix multiplications. Consequently, the speedup observed is often less than the reduction in FLOPs would suggest due to memory access overheads associated with sparse formats (e.g., CSR or COO). However, the CSST algorithm produces structured sparsity to some degree, or can be constrained to do so (e.g., block sparsity), which is more hardware-friendly. The emergence of newer hardware accelerators specifically designed for sparse tensor operations suggests that algorithms like CSST will become increasingly valuable. By maintaining a sparse footprint throughout training, we also lower the memory bandwidth pressure, which is often the true bottleneck in large-scale training. This allows for larger batch sizes or larger model architectures to fit within the same memory budget. The Compressed Sensing framework essentially acts as a data compression layer within the compute pipeline, maximizing the information density of every bit moved from memory to the arithmetic logic units.

7.2 Limitations

Despite the promising results, there are limitations to the current approach. The gradient sensing step, while efficient, still introduces a hyperparameter that governs the trade-off between exploration and exploitation. If the sensing ratio is too low, the algorithm may fail to discover important connections that were initially initialized to zero. Conversely, a high sensing ratio negates the computational benefits. Furthermore, the theoretical guarantees of Compressed Sensing rely on the Restricted Isometry Property, which is difficult to verify explicitly for the measurement matrices generated during neural network training. While empirical evidence suggests the property holds sufficiently well, a rigorous mathematical proof for deep non-linear networks remains an open problem. Another limitation is the complexity of implementation. Unlike static pruning, which is a one-time operation, dynamic sparse training requires modifying the training loop to handle mask updates and sparse gradients. This adds engineering complexity and potential points of failure. Additionally, the convergence stability at extremely high sparsity levels (above 98%) still poses a challenge, as the network becomes extremely sensitive to the removal of even a single weight, resembling a phase transition in percolation theory [15].

8. Conclusion

This paper has presented a novel framework for accelerating the training of large-scale neural networks by integrating principles from Compressed Sensing. By treating the weight matrices as sparse signals and the training process as a recovery problem, we developed the CSST algorithm. This method dynamically adjusts the network topology during training, guided by gradient sensing and iterative thresholding. Our extensive experiments on CIFAR-100 and ImageNet confirm that CSST significantly reduces the computational cost of training while maintaining accuracy levels competitive with dense baselines and superior to existing sparse training methods. The success of this approach highlights the potential of cross-pollinating ideas from signal processing and deep learning. It suggests that the massive over-parameterization currently viewed as necessary for deep learning is, in fact, an artifact of our inability to identify the optimal sparse topology efficiently. Compressed Sensing provides the tools to navigate this high-dimensional space more effectively. Future work will focus on adapting this framework to transformer architectures and exploring hardware-specific constraints to further maximize the real-world efficiency gains. Ultimately,

sparse training algorithms like CSST are essential steps toward sustainable and accessible artificial intelligence.

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