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OPTIMIZATION OF NEURAL NETWORKS ENERGY CONSUMPTION: EFFICIENT APPROACHES TO REDUCING ENERGY USE WITHOUT SACRIFICING PERFORMANCE

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Abstract. This article discusses effective approaches to reducing the energy consumption of neural networks without sacrificing performance and speed. Optimizing the energy consumption of neural networks is a crucial task in machine learning, as it directly impacts the cost and environmental sustainability of machine learning systems. The article will cover various aspects of optimizing the energy consumption of neural networks, including reducing precision, using low-power devices, and energy-efficient algorithms.

Neural networks, which underpin artificial intelligence and machine learning, play a crucial role in various industries, from image processing to data analysis and decision-making. However, as the complexity and size of neural networks grow, their energy consumption also increases, leading to significant electricity costs and negative environmental impacts. In recent years, the energy consumption of neural networks has become a critical issue requiring solutions, as it directly affects the cost and environmental sustainability of machine learning systems.

The importance of energy efficiency in neural networks cannot be overstated. As AI models become more sophisticated, their demand for computational resources escalates. For instance, training a state-of-the-art natural language processing model like GPT-3 requires significant computational power, consuming large amounts of electricity. The carbon footprint of training such models is considerable, with some estimates suggesting that training a single large AI model can emit as much carbon dioxide as five cars in their lifetime.

Optimizing the energy consumption of neural networks is a crucial task in the field of machine learning. Previous studies have proposed various approaches to reducing the energy consumption of neural networks.

One of the main ways to reduce the energy consumption of neural networks is to optimize their architecture. It has been proposed to use deep neural networks with fewer layers, which reduces the number of operations and, consequently, energy consumption. It was also suggested to use lighter operations, such as group normalization instead of batch normalization, which also reduces energy consumption. Architectural choices in neural network design have a significant impact on energy consumption. The architecture determines how efficiently a network can perform computations and handle data, directly influencing the amount of energy required. Optimizing the architecture involves making deliberate decisions about the depth, width, and complexity of the network to balance performance and energy efficiency.

EfficientNet is a family of models designed by Google to achieve better performance with fewer computational resources. The key idea behind EfficientNet is to scale up the network dimensions (depth, width, and resolution) using a compound scaling method. Instead of arbitrarily increasing these dimensions, EfficientNet uses a systematic approach to balance them, which results

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in a more efficient network that achieves higher accuracy with less energy consumption. EfficientNet models have been shown to be more efficient than traditional models like ResNet and Inception, achieving superior performance with fewer parameters and lower computational costs.

MobileNet is another architecture specifically designed for resource-constrained environments like mobile and edge devices. MobileNet uses depthwise separable convolutions, which factorize a standard convolution into a depthwise convolution and a pointwise convolution. This significantly reduces the number of parameters and multiplications, making the network lightweight and energy-efficient. MobileNet variants, such as MobileNetV2 and MobileNetV3, further enhance efficiency through techniques like inverted residuals and linear bottlenecks.

1. Depth: Increasing the depth of a network (adding more layers) can improve its ability to learn complex features but also increases the number of computations and memory usage, leading to higher energy consumption. Deeper networks require more data passes and operations per pass, which can significantly increase energy use.

2. Width: Expanding the width of a network (increasing the number of units per layer) can help capture more features in each layer. However, wider networks also require more parallel computations, increasing the number of parameters and energy consumption. There is a balance to be found, as overly wide networks may not yield proportional performance gains relative to the increase in energy use.

3. Complexity: The complexity of operations within each layer also affects energy consumption. Using more complex operations, such as standard convolutions, can enhance the network's learning capacity but at the cost of higher computational and energy demands. Simplified operations, like those used in MobileNet, reduce energy use but may require careful tuning to avoid sacrificing performance.

Quantizing weights and activations is another effective way to reduce the energy consumption of neural networks. It has been proposed to represent weights and activations as integers instead of floating-point numbers, which reduces the number of floating-point operations and, consequently, energy consumption. The use of quantization to reduce model size, thereby decreasing energy consumption, was also proposed.

Using low-power devices, such as graphics processing units (GPUs) or specialized machine learning chips (TPUs), can also help reduce the energy consumption of neural networks. It was suggested to use GPUs for machine learning operations, which reduces energy consumption compared to traditional central processing units (CPUs).

Reducing computation precision is another way to decrease the energy consumption of neural networks. It was proposed to use lower precision floating-point operations, which reduces the number of operations and, consequently, energy consumption. Using approximations instead of exact calculations was also suggested to reduce energy consumption.

This method has its advantages in terms of energy efficiency, but reducing computation precision can also affect performance. If code uses numbers with lower precision, it can lead to a performance decrease because the computer has to perform more operations to achieve the same result. For example, using 80-bit variables in the code may reduce performance due to the need for additional operations to achieve the same precision.

Using energy-efficient algorithms, such as the stochastic gradient descent algorithm, can also help reduce the energy consumption of neural networks. It was proposed to use the stochastic gradient descent algorithm to reduce the number of operations and, consequently, energy consumption. Data centers used for storing and processing AI data consume a significant amount of electricity. According to the IEA, data centers consumed about 460 terawatt-hours of electricity in 2022, which could increase to 620-1050 terawatt-hours by 2026.

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Dynamic energy management is a way to manage the energy consumption of neural networks depending on their load. It was proposed to use dynamic energy management to reduce energy consumption during periods of low load.

In this article, we have reviewed several effective methods for optimizing the energy consumption of neural networks, which can help reduce their energy use without sacrificing performance and speed. By using these approaches, we can create more efficient and environmentally friendly machine learning systems.

Optimizing the energy consumption of neural networks is an important task that can help reduce electricity costs and negative environmental impacts. In this article, we have reviewed several effective methods for optimizing the energy consumption of neural networks, which can help reduce their energy use without sacrificing performance and speed. By using these approaches, we can create more efficient and environmentally friendly machine learning systems.

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