

The paper introduces SliceGPT, a technique for reducing the size of large language models (LLMs) by eliminating rows and columns from their weight matrices. This method reduces the compute and memory resources needed to run these models without significantly impacting their performance. The paper outlines the context of using sparsification as a means to address the high costs associated with running LLMs and positions SliceGPT as a novel approach within the pruning category of model compression techniques. SliceGPT operates by applying a transformation to the weight matrices of a model which allows for the removal of certain rows or columns with minimal impact on the model's output. This process effectively compresses the model by reducing the dimensionality of the weight matrices and the size of the embeddings, leading to smaller models that require less computational power to run. The authors claim that SliceGPT can reduce up to 25% of a model's parameters while preserving up to 99% of its zero-shot task performance, depending on the specific model being compressed. The paper also introduces the concept of computational invariance in transformer networks, which underpins the effectiveness of SliceGPT. By showing that certain transformations do not change the output of a model, the authors leverage this property to compress the model while maintaining its performance. Experiments conducted on various large models, including LLAMA-270B, OPT 66B, and Phi-2, demonstrate the effectiveness of SliceGPT in reducing model size and computational requirements without significantly compromising performance. The paper concludes with an overview of transformer networks, providing necessary background to understand the technical aspects of the approach and situating SliceGPT within the broader context of efforts to optimize the efficiency of LLMs.