Abstract: The next generation of supercomputers will be exascale high-performance computing (HPC) systems, which are capable of at least 1018 floating-point operations per second, or a factor of 10 times faster than the nation's most powerful supercomputers in use today. The systems will help researchers tackle increasingly complex problems through modeling large-scale systems, such as nuclear reactors or global climate, and simulating complex phenomena. In order to achieve success, these systems must be able to reliably store enormous amounts of high-precision data and perform I/O at an extremely high rate. However, there are serious challenges to build a parallel file system with 10 times performance improvement. Thus, to overcome the gap between computation speed and file system's I/O speed/capacity, HPC researchers have to develop more intelligent and effective ways to reduce data size without losing important information. Data compression provides a good solution for reducing the data size. Although lossless compression can retain all the data information, it suffers from very limited compression ratio. To this end, we have developed a novel lossy scientific data compression framework called SZ, as well as a series of optimization techniques on different hardware (such as GPUs and FPGAs) for various scientific applications (e.g., quantum chemistry, cosmology). These techniques can significantly reduce the data size while maintaining a high fidelity for post-analysis through various accurate error control schemes. On the other hand, lossy compressor developers and users are missing a tool to understand the data alteration after compression in a systematic and reliable way. To address this gap, we have designed and developed generic frameworks (named Z-checker and Foresight), which can be used to systematically evaluate, analyze, and visualize the compression impacts on both application execution and postanalysis, taking into consideration domain features.

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