

OMEinsumContractionOrders: A Julia package for tensor network contraction order optimization

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Summary

OMEinsumContractionOrders (One More Einsum Contraction Orders, or OMECO) is a Julia package (Bezanson et al., 2012) that implements state-of-the-art algorithms for optimizing tensor network contraction orders. OMECO is designed to search for near-optimal contraction orders for exact tensor network contraction, and provides a comprehensive suite of optimization algorithms for tensor network contraction orders, including greedy heuristics, simulated annealing, and tree width solvers. In this paper, we present the key features of OMECO, its integration with the Julia ecosystem, and performance benchmarks.

Statement of need

A *tensor network* is a mathematical framework that represents multilinear algebra operations as graphical structures, where tensors are nodes and shared indices are edges. This diagrammatic approach transforms complex high-dimensional contractions into visual networks that expose underlying computational structure.

The framework has remarkable universality across diverse domains: *einsum* notation (Harris et al., 2020) in numerical computing, *factor graphs* (Bishop & Nasrabadi, 2006) in probabilistic inference, *sum-product networks* in machine learning, and *junction trees* (Villescas et al., 2023) in graphical models. Tensor networks have enabled breakthroughs in quantum circuit simulation (Markov & Shi, 2008), quantum error correction (Piveteau et al., 2024), neural network compression (Qing et al., 2024), strongly correlated quantum materials (Haegeman et al., 2016), and combinatorial optimization problems (Liu et al., 2023).

The computational cost of tensor network contraction depends critically on the *contraction order*—the sequence in which pairwise tensor multiplications are performed. This order can be represented as a binary tree where leaves correspond to input tensors and internal nodes represent intermediate results. The optimization objective balances multiple complexity measures through the cost function:

$$\mathcal{L} = w_t \cdot \text{tc} + w_s \cdot \max(0, \text{sc} - \text{sc}_{\text{target}}) + w_{\text{rw}} \cdot \text{rwc},$$

where w_t , w_s , and w_{rw} represent weights for time complexity (tc), space complexity (sc), and read-write complexity (rwc), respectively. In practice, memory access costs typically dominate computational costs, motivating $w_{\text{rw}} > w_t$. The space complexity penalty activates only when $\text{sc} > \text{sc}_{\text{target}}$, allowing unconstrained optimization when memory fits within available device capacity.

Finding the optimal contraction order—even when minimizing only time complexity—is NP-complete (Markov & Shi, 2008). Algorithms for finding near-optimal contraction orders have been developed and achieve impressive scalability (Gray & Kourtis, 2021; Roa-Villescas et

39 [al., 2024](#)), handling tensor networks with over 10^4 tensors. However, an efficient and reliable
40 implementation of these methods in Julia is still missing.

41 OMECO addresses this gap by offering a unified and extensible interface to a comprehensive suite
42 of optimization algorithms for tensor network contraction orders, including greedy heuristics,
43 simulated annealing, and tree-width-based solvers. OMECO has been integrated into the
44 OMEinsum package and powers several downstream applications: Yao ([Luo et al., 2020](#)) for
45 quantum circuit simulation, GenericTensorNetworks ([Liu et al., 2023](#)) and TensorBranching
46 (TODO: add citation) for combinatorial optimization, TensorInference ([Roa-Villescas &
47 Liu, 2023](#)) for probabilistic inference, and TensorQEC (TODO: add citation) for quantum
48 error correction. These applications are reflected in the ecosystem built around OMECO, as
49 illustrated in [Figure 1](#). This infrastructure is expected to benefit other applications requiring
50 tree or path decomposition, such as polynomial optimization ([Magron & Wang, 2021](#)).

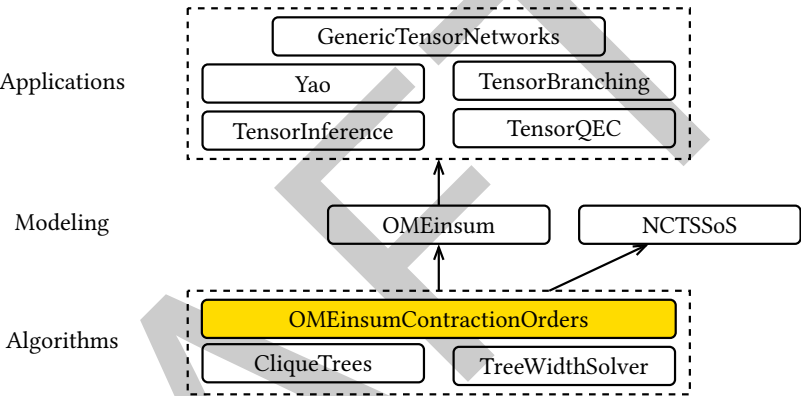


Figure 1: The ecosystem built around OMEinsumContractionOrders and its dependencies. OMECO serves as a core component of the tensor network contractor OMEinsum, which powers applications including Yao (quantum simulation), TensorQEC (quantum error correction), TensorInference (probabilistic inference), GenericTensorNetworks and TensorBranching (combinatorial optimization).

51 **Features and benchmarks**

52 The major feature of OMECO is contraction order optimization. OMECO provides several
53 algorithms with complementary performance characteristics that can be simply called by the
54 `optimize_code` function:

Optimizer	Description
GreedyMethod	Fast greedy heuristic with modest solution quality
TreeSA	Reliable simulated annealing optimizer (Kalachev et al., 2021) with high-quality solutions
PathSA	Simulated annealing optimizer for path decomposition
HyperND	Nested dissection algorithm for hypergraphs, requires KaHyPar or Metis
KaHyParBipartite	Graph bipartition method for large tensor networks (Gray & Kourtis, 2021), requires KaHyPar
SABipartite	Simulated annealing bipartition method, pure Julia implementation

Optimizer	Description
ExactTreewidth	Exact algorithm with exponential runtime (Bouchitté & Todinca, 2001), based on TreeWidthSolver
Treewidth	Clique tree elimination methods from CliqueTrees package

55 The algorithms HyperND, Treewidth, and ExactTreewidth operate on the tensor network's line
56 graph and utilize the CliqueTrees and TreeWidthSolver packages, as illustrated in Figure 1.
57 Additionally, the PathSA optimizer implements path decomposition by constraining contraction
58 orders to path graphs, serving as a variant of TreeSA.

59 These methods balance optimization time against solution quality. Figure 2 displays bench-
60 mark results for the Sycamore quantum supremacy circuit, highlighting the Pareto front
61 where contraction order quality is balanced with optimization runtime. Real-world examples
62 demonstrating applications to quantum circuit simulation, combinatorial optimization, and
63 probabilistic inference are available in the OMEinsumContractionOrdersBenchmark repository.
64 Optimizer performance is highly problem-dependent, with no single algorithm dominating
65 across all metrics and graph topologies.

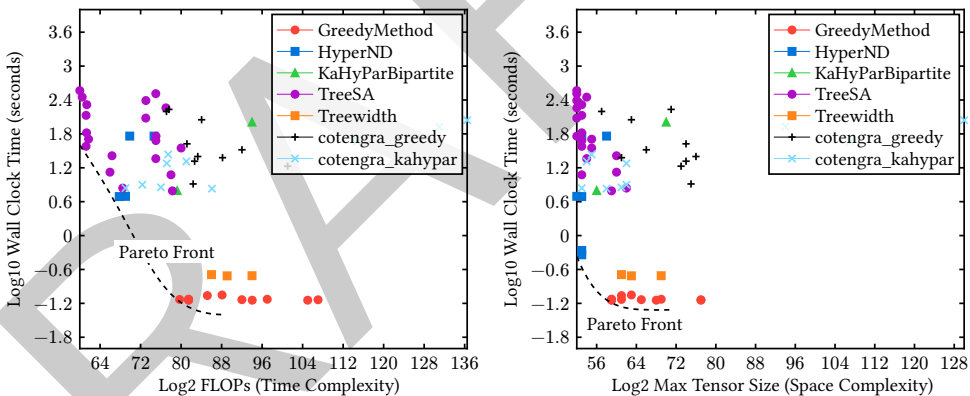


Figure 2: Time complexity (left) and space complexity (right) benchmark results for contraction order optimization on the Sycamore quantum circuit tensor network (Intel Xeon Gold 6226R CPU @ 2.90GHz, single-threaded). The x -axis shows contraction cost, y -axis shows optimization time. Each point represents a different optimizer configuration tested with varying parameters. TreeSA and HyperND achieve the lowest contraction costs, while GreedyMethod offers the fastest optimization time.

66 [JG: TODO: Please also cite CliqueTree paper.]

67 Optimizers prefixed with cotengra_ are from the Python package cotengra (Gray & Kourtis,
68 2021); all others are OMECO implementations. For both optimization objectives (minimizing
69 time and space complexity), OMECO optimizers dominate the Pareto front. Given suffi-
70 cient optimization time, TreeSA consistently achieves the lowest time and space complexity.
71 GreedyMethod provides the fastest optimization but yields suboptimal contraction orders, while
72 HyperND offers a favorable balance between optimization time and solution quality.

73 OMECO has been integrated into the OMEinsum package and powers several downstream
74 applications: Yao (Luo et al., 2020) for quantum circuit simulation, GenericTensorNetworks
75 (Liu et al., 2023) and TensorBranching (TODO: add citation) for combinatorial optimization,
76 TensorInference (Roa-Villescas & Liu, 2023) for probabilistic inference, and TensorQEC for
77 quantum error correction. This infrastructure is expected to benefit other applications requiring
78 tree or path decomposition, such as polynomial optimization (Magron & Wang, 2021).

79 The second feature of OMECO is index slicing, which is a technique to trade time complexity
80 for reduced space complexity by looping over a subset of indices directly. In OMECO, the
81 interface to perform index slicing is `slice_code`, and currently we only support one Slicer,
82 TreeSASlicer, which is implemented the dynamic slicing algorithm based on TreeSA. An
83 example is shown in Figure 3, where the network of the Sycamore quantum circuit is sliced to
84 reduce the space complexity from 52 to 31.

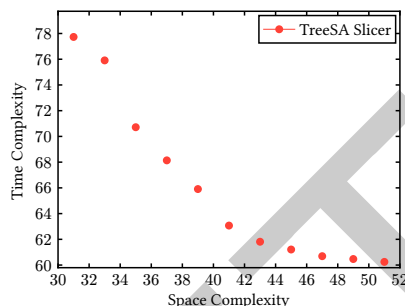


Figure 3: Relation between the time complexity and the target space complexity for the TreeSASlicer. The original network is the Sycamore quantum circuit with an original space complexity of 52.

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