nimCSO: A Nim package for Compositional Space Optimization

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Summary

`nimCSO` is a high-performance tool implementing several methods for selecting components (data dimensions) in compositional datasets, which optimize the data availability and density for applications such as machine learning. Making said choice is a combinatorially hard problem for complex compositions existing in highly dimensional spaces due to the interdependency of components being present. Such spaces are encountered, for instance, in materials science, where datasets on Compositionally Complex Materials (CCMs) often span 20-45 chemical elements, 5-10 processing types, and several temperature regimes, for up to 60 total data dimensions.

At its core, `nimCSO` leverages the metaprogramming ability of the Nim language (Rumpf, 2023) to optimize itself at the compile time, both in terms of speed and memory handling, to the specific problem statement and dataset at hand based on a human-readable configuration file. As demonstrated in the Methods and Performance section, `nimCSO` reaches the physical limits of the hardware (L1 cache latency) and can outperform an efficient native Python implementation over 400 times in terms of speed and 50 times in terms of memory usage (*not* counting interpreter), while also outperforming NumPy implementation 35 and 17 times, respectively, when checking a candidate solution.

`nimCSO` is designed to be both (1) a user-ready tool, implementing two efficient brute-force approaches (for handling up to 25 dimensions), a custom search algorithm (for up to 40 dimensions), and a genetic algorithm (for any dimensionality), and (2) a scaffold for building even more elaborate methods in the future, including heuristics going beyond data availability. All configuration is done with a simple human-readable YAML config file and plain text data files, making it easy to modify the search method and its parameters with no knowledge of programming and only basic command line skills.

Statement of Need

`nimCSO` is an interdisciplinary tool applicable to any field where data is composed of a large number of independent components and their interaction is of interest in a modeling effort, ranging from market economics, through medicine where drug interactions can have a significant impact on the treatment, to materials science, where the composition and processing history are critical to resulting properties. The latter has been the root motivation for the development of `nimCSO` within the ULTERA Project (ultera.org) carried under the US DOE ARPA-E ULTIMATE program, which aims to develop a new generation of ultra-high temperature materials for aerospace applications, through generative machine learning models (Debnath et al., 2021) driving thermodynamic modeling, alloy design, and manufacturing (Li et al., 2024).

41 One of the most promising materials for such applications are the aforementioned CCMs
42 and their metal-focused subset of Refractory High Entropy Alloys (RHEAs) (Senkov et al.,
43 2018), which have rapidly grown since first proposed by (Cantor et al., 2004) and (Yeh et
44 al., 2004). Contrary to most of the traditional alloys, they contain many chemical elements
45 (typically 4-9) in similar proportions in the hope of thermodynamically stabilizing the material
46 by increasing its configurational entropy ($\Delta S_{conf} = \Sigma_i^N x_i \ln x_i$ for ideal mixing of N elements
47 with fractions x_i), which encourages sampling from a large palette of chemical elements. At
48 the time of writing, the ULTERA Database is the largest collection of HEA data, containing
49 over 6,300 points manually extracted from almost 550 publications. It covers 37 chemical
50 elements resulting in extremely large compositional spaces (Krajewski et al., 2024); thus, it
51 becomes critical to answer questions like *"Which combination of how many elements will*
52 *unlock the most expansive and simultaneously dense dataset?"* which has $\binom{37}{15}$ or 10 billion
53 possible solutions.

54 Another significant example of intended use is to perform similar optimizations over large
55 (many millions) datasets of quantum mechanics calculations spanning 93 chemical elements
56 and accessible through OPTIMADE API (Evans et al., 2024).

Methods and Performance

Overview

59 As shown in Figure 1, nimCSO can be used as a user-tool based on human-readable configuration
60 and a data file containing data "elements" which can be any strings representing problem-
61 specific names of, e.g., market stocks, drug names, or chemical formulas. A single command
62 is then used to recompile (`nim c -f`) and run (`-r`) problem (`-d:configPath=config.yaml`)
63 with nimCSO (`src/nimcso`) using one of several methods. Advanced users can also quickly
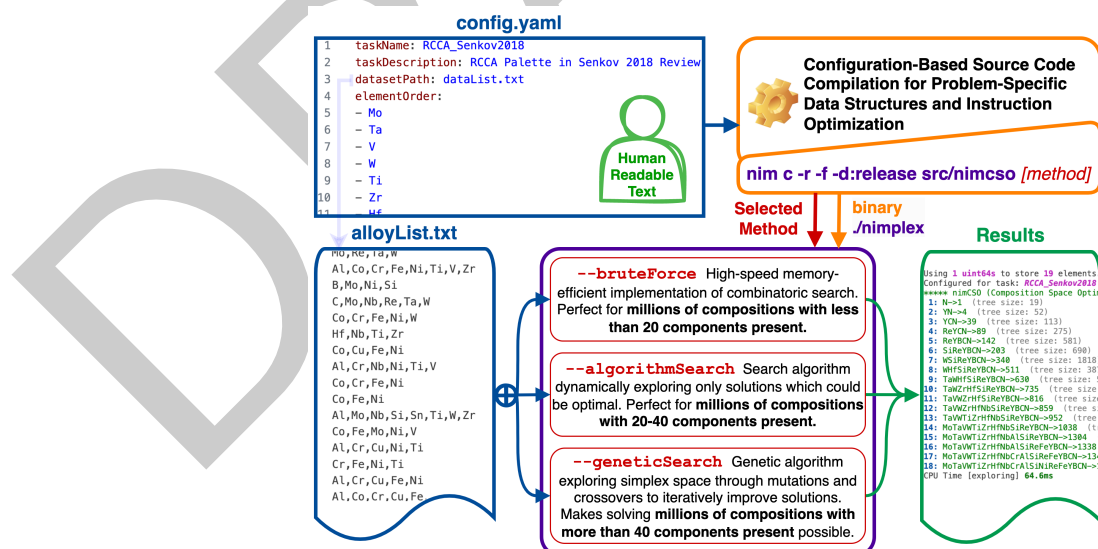64 customize the provided methods with brief scripts using the nimCSO as a data-centric library.

Figure 1: Schematic of core nimCSO data flow with a description of key methods. Metaprogramming is
used to compile the software optimized to the human-readable data and configuration files at hand.

65 Internally, nimCSO is built around storing the data and solutions in one of two ways. The first
66 is as bits inside an integer (`uint64`), which allows for the highest speed and lowest memory
67 consumption possible but is limited to 64 dimensions and does not allow for easy extension to
68 other use cases; thus, as of publication, it is used only in a particular `bruteForceInt` routine.

The second one, used in `bruteForce`, `algorithmSearch`, and `geneticSearch`, implements a custom easily extensible `ElSolution` type containing heuristic value and `BitArray` payload, which is defined at compile time based on the configuration file to minimize necessary overheads. Both encodings outperform typical native Python and NumPy implementations, as shown in Table 1.

Table 1: Benchmarks of (1) average time to evaluate how many datapoints would be lost if 5 selected components were removed from a dataset with 2,150 data points spanning 37 components, averaged over 10,000 runs, and (2) the size of the data structure representing the dataset. Values were obtained by running scripts in `benchmarks` directory on Apple M2 Max CPU.

Tool	Object	Time per Dataset	Time per Entry *(Relative)*	Database Size *(Relative)*
Python[3.11]	set	327.4 µs	152.3 ns *(x1)*	871.5 kB *(x1)*
NumPy[1.26]	array	40.1 µs	18.6 ns *(x8.3)*	79.7 kB *(x10.9)*
nimCSO[0.6]	BitArray	9.2 µs	4.4 ns *(x34.6)*	50.4 kB *(x17.3)*
nimCSO[0.6]	uint64	0.79 µs	0.37 ns *(x413)*	16.8 kB *(x52)*

Brute-Force Search

The brute-force search is a naïve method of evaluating all possibilities; however, its near-zero overhead can make it the most efficient for small problems. In this implementation, all entries in the *power set* of N considered elements are represented as a range of integers from 0 to $2^N - 1$, and used to initialize `uint64`/`BitArray`s on the fly. To minimize the memory footprint of solutions, the algorithm only keeps track of the best solution for a given number of elements present in the solution. Current implementations are limited to 64 elements, as it is not feasible beyond approximately 30 elements; however, the one based on `BitArray` could be easily extended if needed.

Algorithm-Based Search

The algorithm implemented in the `algorithmSearch` routine, targeting high dimensional problems (20-50), iteratively expands and evaluates candidates from a priority queue (implemented through an efficient binary heap ([Williams, 1964](#))) while leveraging the fact that *the number of data points lost when removing elements A and B from the dataset has to be at least as large as when removing either A or B alone* to delay exploration of candidates until they can contribute to the solution. Furthermore, to (1) avoid revisiting the same candidate without keeping track of visited states and (2) further inhibit the exploration of unlikely candidates, the algorithm *assumes* that while searching for a given order of solution, elements present in already expanded solutions will not improve those not yet expanded. This effectively prunes candidate branches requiring two or more levels of backtracking. In the authors' tests, this method has generated the same results as `bruteForce`, except for occasional differences in the last explored solution.

Genetic Search

Beyond 50 components, the [algorithm-based](#) method will likely run out of memory on most personal systems. The `geneticSearch` routine resolves this issue through an evolution strategy to iteratively improve solutions based on custom `mutate` and `crossover` procedures. Both are of uniform type ([Goldberg, 1989](#)) with additional constraint of Hamming weight ([Knuth, 2009](#)) preservation in order to preserve number of considered elements in parents and offspring. In `mutate` this is achieved by using purely random bit swapping, rather than more common flipping, as demonstrated in the Figure 2.
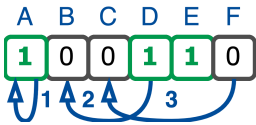
Figure 2: Schematic of `mutate` procedure where bits are swapping randomly, so that (1) bit can swap itself, (2) bits can swap causing a flip, or (3) bits can swap with no effect.

Meanwhile, in `crossover`, this constraint is satisfied by passing overlapping bits directly, while non-overlapping bits are shuffled and distributed at positions present in one of the parents, as shown in Figure 3.

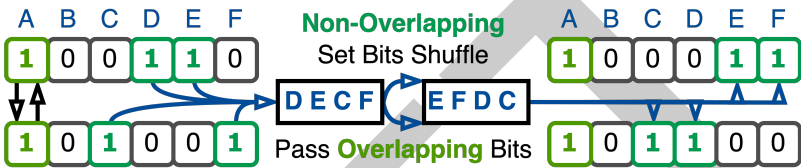**Figure 3:** Schematic of uniform `crossover` procedure preserving Hamming weight implemented in `nimCSO`.

The above are applied iteratively, with best solutions carried to next generation, until the solution converges or the maximum number of iterations is reached. Unlike the other methods, the present method is not limited by the number of components and lets user control both time and memory requirements, either to make big problems feasible or to get a good-enough solution quickly in small problems. However, it comes with no optimality guarantees.

Use Examples

The tool comes with two pre-defined example problems to demonstrate its use. The first one is defined in the default `config.yaml` file and goes through the complete dataset of 2,150 data points spanning 37 components in `dataList.txt` based on the ULTERA Dataset ([Debnath et al., 2021](#)). It is intended to showcase `algorithmSearch`/`-as` and `geneticSearch`/`-gs` methods, as brute-forcing would take around one day. The second one is defined in `config_rhea.yaml` and uses the same dataset but a limited scope of components critical to RHEAs ([Senkov et al., 2018](#)) and is intended to showcase `bruteForce`/`-bf` and `bruteForceInt`/`-bfi` methods. With four simple commands (see Table 2), the user can compare the methods' performance and the solutions' quality.

Table 2: Four example tasks alongside typical CPU time and memory usage on Apple M2 Max.

Task Definition (`nim c -r -f -d:release ...`)	Time (s)	Memory (MB)
`-d:configPath=config.yaml src/nimcso -as`	302s	488 MB
`-d:configPath=config.yaml src/nimcso -gs`	5.8s	3.2 MB
`-d:configPath=config_rhea.yaml src/nimcso -as`	0.076s	2.2 MB
`-d:configPath=config_rhea.yaml src/nimcso -gs`	0.429s	2.1 MB
`-d:configPath=config_rhea.yaml src/nimcso -bf`	4.171s	2.0 MB
`-d:configPath=config_rhea.yaml src/nimcso -bfi`	0.459s	2.0 MB

In case of issues, the help message can be accessed by running the tool with `-h` flag or by refering to documentation at amkrajewski.github.io/nimCSO.

Contributions

A.M.K. was reponsible for conceptualization, methodology, software, testing and validation, writing of manuscript, and visualization; A.D. was responsible for testing software and results in training machine learning models; A.M.B., W.F.R., Z-K.L. were responsible for funding acquisition, review, and editing. Z-K.L. was also supervising the work.

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