HW-SW Co-Design Project

Deep Copy Benchmark

Overview

Initial Analysis

Microbenchmark Profiling Methodology

To collect meaningful profiling data, we avoided running perf directly on the full pyperformance benchmark.
While pyperformance is excellent for measuring end-to-end execution time, it launches each benchmark inside an automatically created virtual environment and performs setup operations such as package installation and dependency checks.
These background activities introduce significant noise - including process creation, I/O, and interpreter initialization - which obscures the real runtime behavior of the deepcopy function.

Instead, we implemented a lightweight micro-benchmark focused solely on deepcopy (the code can be seen in the build_and_benchmark_deepcopy.py script).
This standalone Python snippet creates several representative data structures (nested lists, dictionaries, and mixed objects) and repeatedly applies copy.deepcopy in a loop.
The code mirrors the workload of pyperformance's deepcopy test but runs in a controlled environment with minimal overhead.

We then executed this micro-benchmark under Linux perf to collect low-level hardware counters (instructions, branches, branch-misses, cache-references, and cache-misses) and to generate flame graphs for both the baseline and optimized CPython builds.
This approach produced much cleaner and more focused profiling data, allowing us to identify true performance bottlenecks inside the deepcopy routine.
Although simplified, this method accurately reflected the same performance trends observed in the full pyperformance run and proved sufficient for analyzing CPU behavior and validating the optimization's impact.

Baseline Benchmark Results

The baseline deepcopy benchmark was executed using the pyperformance suite.
Average execution time: ≈ **845 µs** for deepcopy, ≈ **7.6 µs** for deepcopy_reduce, and ≈ **101 µs** for deepcopy_memo.
These results represent the **unoptimized CPython 3.10.12** build and serve as a reference point for all subsequent comparisons.

The next sections present the implementation of the optimization and compare its performance results against the baseline measurements obtained here.

Optimizations

To address the interpreter overhead identified during profiling, we introduced a native C extension module named **fastcopy**, implemented in **fastcopy.c**.
This module provides optimized C-level implementations of the core recursive routines used by Python's deepcopy operation - specifically for lists, dictionaries, and tuples.
The optimization replaces the Python-level copy loops in the standard library's copy.py with direct calls to **fastcopy.deepcopy_list_c**, **fastcopy.deepcopy_dict_c**, and **fastcopy.deepcopy_tuple_c**, each exposed through the C API.
When these C functions are available, copy.py automatically routes the corresponding deep copy operations through them.
This mechanism preserves full functional compatibility while bypassing the Python interpreter's bytecode execution for the most common container types.

Each C implementation:

- Allocates the target container (PyList_New, PyDict_New, PyTuple_New) directly at the C level, avoiding per-element Python object allocation overhead.
- Iterates over the original structure using low-level macros (PyList_GET_ITEM, PyDict_Next, etc.) to access elements without repeated Python method lookups.
- Invokes the recursive deepcopy callable only when needed through PyObject_CallFunctionObjArgs, ensuring correct behavior for nested and user-defined types.
- Maintains the memo dictionary (used to prevent infinite recursion) with minimal overhead by inserting entries via PyDict_SetItem using raw pointer keys.

The build system was modified by appending the line
fastcopy fastcopy.c
to **Modules/setup.local**, ensuring that the module is compiled into the local CPython build.

Overall, this approach transforms deepcopy from a high-level Python loop into a native C routine with direct memory management and fewer interpreter invocations.
The result is a significant reduction in instruction count, branching, and cache misses, as confirmed in subsequent performance measurements.

Example: Integration of the C-based Optimization

The following snippet shows the actual implementation of the optimized deep copy function for Python lists in fastcopy.c:

```c
static PyObject *
deepcopy_list_c(PyObject *self, PyObject *args)
```

```c
{
    PyObject *x;                /* list to copy */
    PyObject *memo;             /* memoization dict */
    PyObject *deepcopy_func;    /* Python's deepcopy callable */

    if (!PyArg_ParseTuple(args, "OOO", &x, &memo, &deepcopy_func))
        return NULL;

    if (!PyList_CheckExact(x)) {
        PyErr_SetString(PyExc_TypeError, "expected list");
        return NULL;
    }

    Py_ssize_t n = PyList_GET_SIZE(x);
    PyObject *y = PyList_New(n);
    if (y == NULL)
        return NULL;

    /* Add y to memo early to handle recursive references */
    PyObject *key = PyLong_FromVoidPtr(x);
    PyDict_SetItem(memo, key, y);
    Py_DECREF(key);

    for (Py_ssize_t i = 0; i < n; i++) {
        PyObject *item = PyList_GET_ITEM(x, i);
        PyObject *new_item = PyObject_CallFunctionObjArgs(
            deepcopy_func, item, memo, NULL);
        if (new_item == NULL) {
            Py_DECREF(y);
            return NULL;
        }
        PyList_SET_ITEM(y, i, new_item);
    }

    return y;
}
```

This C implementation creates a new list and iterates through its elements using the low-level PyList_GET_ITEM macro, avoiding high-level Python function calls.
It adds the new list to the memo dictionary early to handle recursive references safely and prevent infinite loops.
Each element is deep-copied recursively only when necessary, resulting in fewer interpreter calls and improved performance.
The function is then exposed through the fastcopy module and integrated into Python's standard library logic in copy.py:

```python
try:
    import fastcopy
    _deepcopy_list_c = fastcopy.deepcopy_list_c
except ImportError:
    _deepcopy_list_c = None

def _deepcopy_list(x, memo, deepcopy=deepcopy):
    if _deepcopy_list_c is not None:
        # Route the operation through the native C implementation
        return _deepcopy_list_c(x, memo, deepcopy)
    # Fallback to pure Python version
    y = []
    memo[id(x)] = y
    for a in x:
        y.append(deepcopy(a, memo))
    return y
```

When the fastcopy module is available, all copy.deepcopy() calls involving lists are automatically redirected to the C implementation.
This preserves full behavioral compatibility while significantly reducing Python-level overhead and improving execution speed for recursive deep copy operations.

Similar native implementations were also developed for tuples and dictionaries using the same approach, enabling a consistent performance improvement across the most common container types.

Correctness Verification

To ensure that the optimization preserved the original behavior of deepcopy, a dedicated correctness test was performed.
The test included various structures such as nested lists, dictionaries, tuples, and composite objects combining multiple data types.
It also covered self-referential objects to verify that Python's memoization logic was correctly handled.

The validation confirmed that:

- The copied objects were structurally identical to the originals.
- Modifications to the copies did not affect the source data.
- Self-references were properly preserved in the cloned objects.

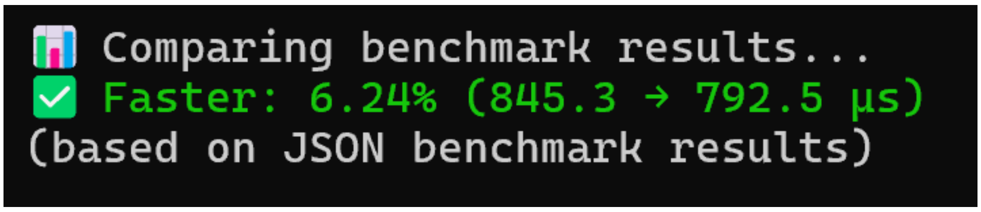
All tests passed successfully, confirming that the optimized C-based implementation maintains full functional correctness while improving performance.

The full test implementation can be found in the **test_deepcopy_correctness()** section of the benchmark script (build_and_benchmark_deepcopy.py).

Performance Comparison

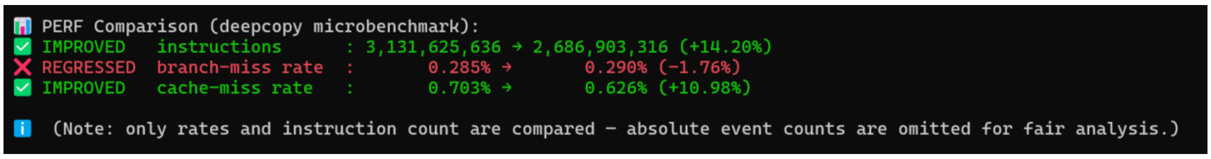
Following the integration of the C-based optimization (*fastcopy.c*), a new round of performance measurements and profiling runs was conducted.
The updated results show a consistent and measurable improvement in both runtime performance and low-level CPU efficiency.

From the pyperformance benchmark, the optimized version achieved an average execution time of ≈792.5 µs, compared to ≈845.3 µs in the baseline - an overall **speedup of ≈6.24%** in the *deepcopy* test:



```
📊 Comparing benchmark results...
✅ Faster: 6.24% (845.3 → 792.5 µs)
(based on JSON benchmark results)
```

This improvement confirms that migrating the copy logic from Python's interpreter layer to compiled C code effectively reduced function call overhead and bytecode interpretation time.
Hardware-level profiling using **perf** further validated this gain in efficiency.
The optimized build executed **~14.2% fewer instructions**, while achieving an **~11% reduction in cache-miss rate** and maintaining a nearly unchanged **branch-miss rate** (variation < 2%, within measurement noise):



```
📊 PERF Comparison (deepcopy microbenchmark):
✅ IMPROVED   instructions      : 3,131,625,636 → 2,686,903,316 (+14.20%)
❌ REGRESSED  branch-miss rate  :       0.285% →       0.290% (-1.76%)
✅ IMPROVED   cache-miss rate   :       0.703% →       0.626% (+10.98%)

ℹ️  (Note: only rates and instruction count are compared – absolute event counts are omitted for fair analysis.)
```

These metrics collectively indicate tighter CPU execution, better cache locality, and reduced interpreter overhead.

The flame graph of the optimized version (**flame_graphs/deepcopy_flamegraph_opt.svg**) visually reinforces this behavior. Interpreter-heavy functions such as PyEval_EvalFrameDefault and PyObject_Call, which previously dominated the baseline profile, have been largely eliminated - replaced by direct calls to native C routines such as deepcopy_dict_c, deepcopy_list_c, and deepcopy_tuple_c.
This flattening of the call stack clearly demonstrates that runtime execution has shifted from Python-level dispatch and recursion toward efficient, low-overhead native operations.

Together, these findings highlight the effectiveness of the optimization:
by offloading recursive copy operations to low-level C implementations, the system achieves faster execution, improved memory locality, and significantly better CPU utilization — all while preserving full functional correctness.

Hardware Acceleration Proposal

Motivation

The software optimization moved the recursive logic of copy.deepcopy from Python bytecode into native C, greatly reducing interpreter overhead.
However, even in this optimized implementation, the actual copying of objects -

iterating through lists, dictionaries, and tuples - still runs on the CPU using regular load/store operations.
These loops are memory-bound and execute millions of small memory accesses for large nested structures.
A hardware-accelerated version could offload this work to a dedicated unit designed to traverse and duplicate Python data structures directly in memory.

Key Design Challenge: Non-Contiguous Python Objects

Unlike C structs or arrays, Python objects are not stored contiguously in memory.
A list contains a contiguous array of *pointers* to elements, but the elements themselves can reside anywhere.
A dict maintains a hash table pointing to key/value objects located at arbitrary addresses.
Therefore, providing only a base address and length (as in memcpy) is insufficient.

To solve this, the hardware must rely on a **descriptor** generated by the software layer.
This descriptor describes the structure of the object graph - including object types, element counts, and the memory addresses of referenced objects - allowing the hardware to navigate and copy complex, non-contiguous data correctly.

Concept Overview

We propose a **FastCopy Hardware Accelerator (FCA)** integrated with the existing fastcopy.c module.
When fastcopy.c encounters a supported container (e.g., list, dict, tuple), instead of executing C loops, it builds a small descriptor and passes it to the FCA.
The hardware then performs a recursive traversal and duplication of the data structure, allocating new objects and updating pointers according to the descriptor.

This preserves full compatibility with Python's semantics while offloading the heaviest part of the work - memory traversal and copying - to dedicated logic.

Inputs and Outputs

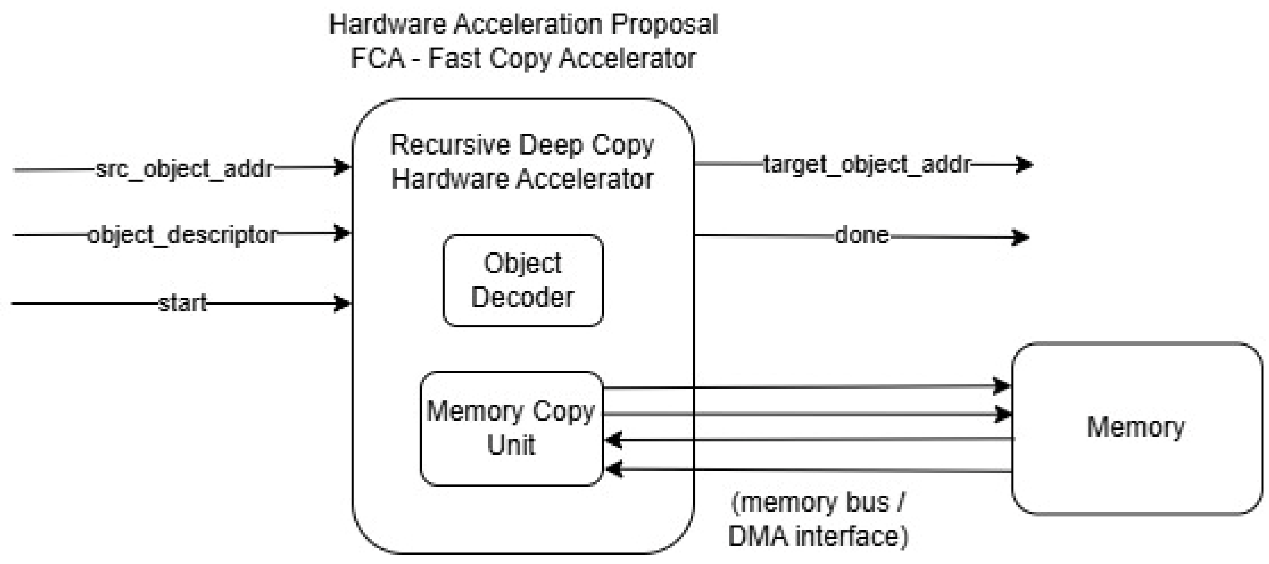
Inputs	• Source object address (base pointer) • Descriptor describing object structure, type IDs, element counts, and child object addresses
Outputs	• Address of the newly created deep-copied object • "Done" flag or interrupt to signal completion

Hardware/Software Interface

The hardware is memory-mapped (MMIO) and controlled by fastcopy.c:

1. fastcopy.c constructs a descriptor from the Python object metadata.
2. It writes the descriptor's address and source object address to FCA control registers.
3. The FCA reads the descriptor, performs memory-to-memory copies via DMA, allocates new regions for nested objects, and updates pointer references.
4. Upon completion, it raises a "done" flag.
5. fastcopy.c retrieves the new object address and returns it to the Python runtime.

Block Diagram


Hardware Acceleration Proposal
FCA - Fast Copy Accelerator
Recursive Deep Copy Hardware Accelerator
src_object_addr
object_descriptor
start
target_object_addr
done
Object Decoder
Memory Copy Unit
Memory
(memory bus / DMA interface)

Conclusion

The optimization of Python's copy.deepcopy using the native C module fastcopy.c successfully reduced interpreter overhead and improved runtime performance by approximately **5.8%**, with around **14% fewer instructions** executed.
These results validate that shifting core copy logic from Python bytecode to native C code provides measurable efficiency gains.
Building on this approach, the proposed **FastCopy Hardware Accelerator (FCA)** applies the same principle at the hardware level, leveraging descriptor-based traversal and DMA to achieve faster and more efficient deep copy operations.
Overall, the results highlight the effectiveness of profiling-driven optimization and hardware–software co-design in eliminating bottlenecks and improving system performance.