



# Iterating Pointers: Enabling Static Analysis for Loop-based Pointers

ANDREA LEPORI, Dept. of Computer Science, ETH Zurich, Zurich, Switzerland

ALEXANDRU CALOTOIU, Dept. of Computer Science, ETH Zurich, Zurich, Switzerland

TORSTEN HOEFLER, Dept. of Computer Science, ETH Zurich, Zurich, Switzerland

---

Pointers are an integral part of C and other programming languages. They enable substantial flexibility from the programmer's standpoint, allowing the user fine, unmediated control over data access patterns. However, accesses done through pointers are often hard to track and challenging to understand for optimizers, compilers, and sometimes, even for the developers themselves because of the direct memory access they provide. We alleviate this problem by exposing additional information to analyzers and compilers. By separating the concept of a pointer into a data container and an offset, we can optimize C programs beyond what other state-of-the-art approaches are capable of, in some cases even enabling auto-parallelization. Using this process, we are able to successfully analyze and optimize code from OpenSSL, the Mantevo benchmark suite, and the Lempel–Ziv–Oberhumer compression algorithm. We provide the only automatic approach able to find all parallelization opportunities in the HPCCG benchmark from the Mantevo suite the developers identified, and we even outperform the reference implementation by up to 18% as well as speed up the PBKDF2 algorithm implementation from OpenSSL by up to 11×.

CCS Concepts: • **Software and its engineering** → **Source code generation**; • **Computing methodologies** → **Parallel computing methodologies**;

Additional Key Words and Phrases: Pointer analysis, automatic parallelization

## ACM Reference Format:

Andrea Lepori, Alexandru Calotoiu, and Torsten Hoefer. 2025. Iterating Pointers: Enabling Static Analysis for Loop-based Pointers. *ACM Trans. Arch. Code Optim.* 22, 1, Article 4 (March 2025), 25 pages. <https://doi.org/10.1145/3701993>

---

## 1 Introduction

C is a widely used programming language, one that is heavily relied upon in many codebases. In 2022, on GitHub, C and C++ accounted together for 4.6M repositories [29], this being a 23.5% growth compared to the previous year [30]. According to the TIOBE index [53], C is the second most popular programming language.

---

New article, not an extension of a conference paper.

This project has received funding from EuroHPC-JU under grant agreement DEEP-SEA No. 95560 and by the European Research Council (ERC) under the European Union's Horizon 2020 program (grant agreement PSAP, No. 101002047). This work was partially supported by the ETH Future Computing Laboratory (EFCL), financed by a donation from Huawei Technologies.

Authors' Contact Information: Andrea Lepori, Dept. of Computer Science, ETH Zurich, Zurich, Switzerland; e-mail: andrea.lepori@inf.ethz.ch; Alexandru Calotoiu, Dept. of Computer Science, ETH Zurich, Zurich, Switzerland; e-mail: acalotoiu@inf.ethz.ch; Torsten Hoefer, Dept. of Computer Science, ETH Zurich, Zurich, Switzerland; e-mail: htor@inf.ethz.ch.



This work is licensed under a Creative Commons Attribution-ShareAlike International 4.0 License.

© 2025 Copyright held by the owner/author(s).

ACM 1544-3973/2025/03-ART4

<https://doi.org/10.1145/3701993>

Accessing the same pointer at a different index does not guarantee that different data is accessed — pointers can move during execution. Accessing the same pointer at the same location with access to different data. Creation of false positives in data dependency analysis.

<pre>p[i+1] = 0; // array-style access p++;      // pointer moves p[i] = 42; // array-style access to same memory</pre>	<pre>for (int i=0; i&lt;cplen*n; i+=cplen) {   for (int k=0; k&lt;cplen; k++) {     p[k] = p[k] ^ data[k]; // no loop dependence   }   p += cplen; // outer iteration on different data }</pre>
<small>Snippet of the P8KDF2 implementation from OpenSSL</small>	

Fig. 1. Two example codes where we can have false positives and negatives with pointer accesses.

The C language was developed in the 1970s at about the same time as the first microprocessor [21, 49]. Parallel computing only became widespread decades later, driven by the end of Dennard scaling [13, 45]. Hardware efforts to continue growth following Moore’s Law past the power wall lead to a renewed focus on parallel computing as a way to continue improving performance [12, 28]. C was not designed with parallel programming in mind, as its inception was much earlier than the explosion of parallel computing. Libraries provide support for parallel paradigms—such as OpenMP [23] or MPI [44]—but add a difficult-to-manage layer of complexity. The flexibility and low-level nature of C code make debugging challenging, even more so when the code is executed in parallel [16, 22]. This makes parallelizing code a long and complex process.

Frameworks such as Polly [31] and Pluto [18] promise automatic parallelism—these are, however, limited to **static control parts (SCoPs)**. The Intel compiler offers the `icc parallel` mode that can identify and auto-parallelize several predefined programming patterns. Data-centric methods [20] try to push the boundary even further by leveraging complex dataflow analysis techniques to better understand data movement and dependencies. On modern systems, data movement is the most expensive operation in most programs, concerning both time and energy consumption [36], and tends to be the biggest bottleneck in computations [47]. Many frameworks and compilers such as HPVM [40], Halide [48], Jax [27], and DaCe [15] leverage dataflow analysis extensively in their pipeline.

The major obstacle in the static analysis of data accesses is, unfortunately, the use of pointers. Though they are an integral part of the C language, they often become a barrier on the road to performance. The Intel C/C++ programming guidelines [2] also suggest to use array notation rather than pointers. This issue can be seen in the two examples in Figure 1. On the right side of the figure, we can see that the inner loop only has independent data accesses, and modern compilers are able to detect that. But no compiler we tested was able to detect that the outer loop has no data dependency. Every access done with `p[k]` is different because of the pointer movement in the outer loop. Current analysis methods do not consider this type of access, as it would require complex and expensive pointer tracking, and even then it would require a correlation between the pointer movement and loop iterations.

Our solution aims to address this challenge by tracking data containers (as opposed to pointers) across the entire program. We then split pointers into the data container and an integer index to it. This effectively makes data accesses explicit while preserving execution semantics, enabling better analyzability of the code. A state-of-the-art data-centric compiler can then attempt to parallelize and improve the performance of the code. The implementation of our methods is explained in Section 2. Afterwards, in Section 3, we discuss the limitations and motivation behind them. In Section 4, we will discuss possible solutions to mitigate the limitations, showing some specific transformations handling special cases.

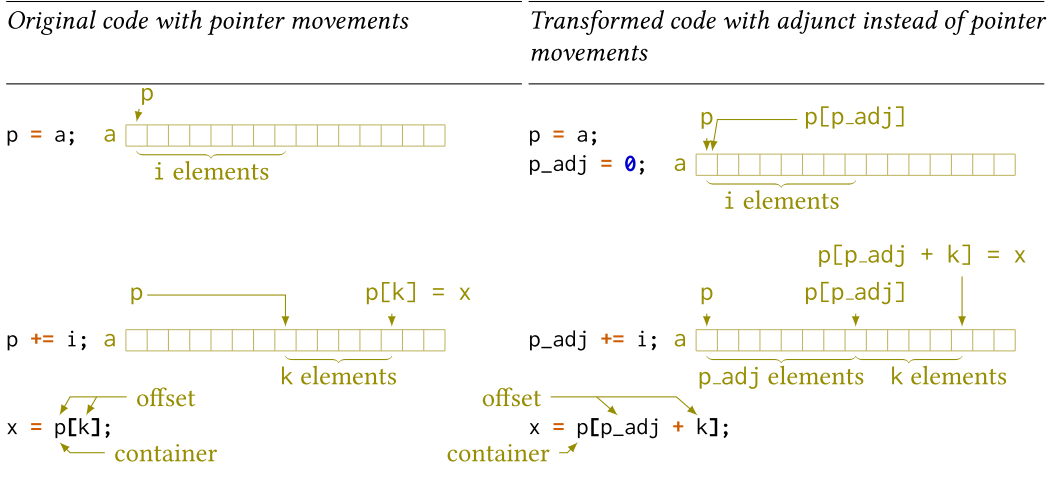


Fig. 2. Representation of data access patterns with pointer movement (left) and static accesses with *adjunct* (right). Annotated with the accessed memory locations and pointer values. In the case of pointer movements, the pointer is both the container and the offset, while with the *adjunct* the pointer is only the container.

*Contributions*

- We introduce a novel method to statically split pointers into a data container and an index to it, creating explicit data accesses to aid further analysis.
- We generate a parallel version of the Mantevo HPCCG benchmark, automatically finding all parallelization opportunities the benchmark developers envisioned manually. Our automatic workflow outperforms the manually tuned version by up to 6%.
- We automatically parallelize the previously serial PBKDF2 algorithm implemented in OpenSSL and obtain up to an 11× speedup.

**2 Pointer Disaggregation**

We propose a static method to improve the analyzability of pointers that are used as iterators over data containers. We first provide a high-level overview explaining our method. We follow with some notes toward a proof and the description of the technical implementation. Then, we compare our method with previous work. We also provide some examples and results to show the value of our transformation.

**2.1 High-level Overview**

Pointers are used both as handles for data containers and to iterate over them. By splitting these two semantically different use cases, we intend to improve element-sensitive analysis of pointer accesses. For each pointer, we create an *adjunct* int variable that represents the offset from the start of the data container. Note that the type of the *adjunct* should be big enough to address every element plus one in the connected data-container. The goal of the *adjunct* is to allow iteration over the data container without modifying the handle used to access said data container. We need the *adjunct* type to be plus one larger than the size of the data container, as with loops containing `*p++`, we could have the need to get the address after the last element.

Figure 2 shows a high-level example of how the *adjunct* is used. We can see from the figure that the value of `x` after both executions is the same. For general code, it is important to note that `p[i]` is semantically equivalent to `*(p + i)`, as per C99 standard [35]. In Figure 3, we present a minimal

<i>C representation</i>	<i>ASM representation</i>	
<pre>for (int i=0; i&lt;n; i++) {   p[0] = i + 1;   p++; }</pre>	<pre>.L4: add    eax, 1    ; i++ add    rdx, 4    ; p++ mov    DWORD PTR [rdx-4], eax cmp    eax, r14d ; i &lt; n jne    .L4</pre>	<p>loop iterator → <i>eax</i>  pointer iterator → <i>rdx</i>  <i>n</i> value → <i>r14d</i></p>
<p><i>adjunct transformation</i> ↓      No pointer increment ⇒ one less instruction ↓</p>		
<pre>for (int i=0; i&lt;n; i++) {   p[p_adj + 0] = i + 1;   p_adj++; }</pre>	<pre>.L4: mov    DWORD PTR [r12-4+rax*4], eax add    rax, 1    ; i++ cmp    rdx, rax ; i &lt; n jne    .L4</pre>	<p>loop iterator → <i>rax</i>  pointer iterator ↑  container base address → <i>r12</i>  <i>n</i> value → <i>rdx</i></p>

Fig. 3. Difference in the assembly representation (compiled with gcc 12.2 and -O2) between a code using pointer movement and one with static access after the *adjunct* is introduced.

example to show the value of introducing the *adjunct* variable. We provide the resulting assembly to show that when using the *adjunct*, the compiler is able to correctly identify that  $p_{adj}$  is only used as an iterator similar to  $i$  and merges the two, resulting in more compact, efficient code.

The *adjunct* transformation enhances code analyzability and exposes additional parallelization opportunities. Such transformed pointers are equivalent to arrays, in that the symbol represents a data container that is statically known. The *adjunct* variable dictates how the pointer is accessed. Because it is an `int` variable, there are more compiler analysis methods available to track the value. Inside loops a compiler could apply **Loop Strength-Reduction (LSR)** to simplify addressing computations. Note that this can only be done after the *adjunct* transformation is applied, as LSR only acts on integer values and not addresses (pointers). If instead the *adjunct* variable is never used—if a pointer is never moved, for example—then the compiler will be able to optimize away the *adjunct* with constant propagation, resulting in no performance losses. A summary of the transformation is described in Figure 4. To note is that the expression  $p = q \diamond x$  is a combination of  $p = q$ ;  $q = q \diamond x$ . Because of this fact, we do not detail this case in the following sections, as it follows from the other statements.

The *adjunct* type is deliberately a *signed* integer to replicate the behavior of actual pointer movement. This is because of the non-wrapping behavior when the *adjunct* becomes negative. It is worth noting that accessing a pointer with a negative offset might be considered valid behavior under certain circumstances. For instance, if a programmer is confident that the memory is initialized within the same program, such as when an opaque library provides a pointer within an array, and the programmer is aware of the underlying structure.

Function arguments and calls undergo minimal modifications. When a function is called, it is treated as a dereference, and we pass the pointer with the *adjunct* offset applied. The function argument declarations remain unchanged, meaning that the *adjunct* information is lost after the function call. This is generally not an issue, as subroutines often do not require the additional information. Moreover, this problem is mitigated by the compiler’s automatic inlining or by manually annotating functions to force inlining, thereby eliminating the function call.

## 2.2 Notes toward a Proof

We provide a proof sketch that the transformation showed in Figure 4 does not modify the accesses done with pointers. First, for initialization of a pointer, let  $p$  be a pointer to some data. Then, let  $p_{adj}$

Original code	Modified code	Original code	Modified code
<code>int* p;</code>	<code>int* p;</code> <code>int p_adj = 0;</code>	<code>f(p);</code>	<code>f(p + p_adj);</code>
<code>*p</code>	<code>p[p_adj]</code>	<code>void f(int* p) {</code>	<code>void f(int* p) {</code> <code>int p_adj = 0;</code>
<code>p[x]</code>	<code>p[x + p_adj]</code>	<code>// body</code>	<code>// body</code>
<code>p = p <math>\diamond</math> x;</code> <code>or p <math>\diamond</math>= x;</code>	<code>p_adj = p_adj <math>\diamond</math> x;</code>	<code>int k = *p;</code>	<code>int k = p[p_adj];</code>
<code>p = q;</code>	<code>p = q;</code> <code>p_adj = q_adj;</code>	<code>}</code>	<code>}</code>
<code>p = q <math>\diamond</math> x;</code>	<code>p = q;</code> <code>p_adj = q_adj <math>\diamond</math> x;</code>		

Fig. 4. Transformation summary to improve pointer analyzability. Both  $p$  and  $q$  are `int` pointers (`int* p`, `q`),  $x$  is an `int` expression, and  $\diamond$  is any integer binary operator. Note that the data-type `int` is only for explanation purposes and can be substituted with any other type. The *adjunct*-type `int` can be interchanged with any integer type that fits the size of the data-container.

be a new unique integer variable not already present in the program and initialized to zero when the memory of the pointer is first initialized, i.e., we have  $p = \text{malloc}(\dots); p_{adj} = 0$ , where  $p_{adj}$  was not previously present in the variable definitions. This is a new variable definition without any name conflict, hence it will not influence other parts of the program.

Let  $S$  be an arbitrary  $n$  length sequence of statements s.t.

$$S = (p := p + x_i | x_i \in \mathbb{Z}, 0 \leq i < n).$$

Then, we define the syntax  $S; p$  by using the sequential operator `;` with a variable name at the end as the value of  $p$  after execution of  $S$ . By our definition, we have that:

$$(S; p) = p + \sum_{i=0}^n x_i.$$

Let  $S'$  be an  $n$  length sequence of statements (note that  $x_i$  are the same values as in  $S$  and in the same order).

$$S' = (p_{adj} := p_{adj} + x_i | x_i \in \mathbb{Z}, 0 \leq i < n)$$

As before, by definition, we have that

$$(S'; p_{adj}) = p_{adj} + \sum_{i=0}^n x_i.$$

We can see that

$$(S; p) = p + \sum_{i=0}^n x_i = p + p_{adj} + \sum_{i=0}^n x_i - p_{adj} = p + (S'; p_{adj}) - p_{adj}.$$

By using the sequential operator `;` we define a program sequence that defines the pointer  $p$ , integer  $p_{adj}$ , and executes all statements in  $S$ . This represents an arbitrary program from the definition

to the access of a pointer  $p$  with arbitrary pointer movements in between.

$$\begin{aligned} (p := \text{malloc}(\dots); (p_{adj} := 0; (S; p))) &= (p := \text{malloc}(\dots); (p_{adj} := 0; (p + (S'; p_{adj}) - p_{adj}))) \\ &= (p := \text{malloc}(\dots); (p_{adj} := 0; (p + (S'; p_{adj})))) \end{aligned}$$

We note that  $(S'; p) = p$  and  $(S; p_{adj}) = p_{adj}$ , as the statements do not affect the evaluated variable. Then, we have that if we substitute any execution  $p = p + x_i$  with  $p_{adj} = p_{adj} + x_i$  i.e., executing  $S'$  instead of  $S$ , then

$$\begin{aligned} (p := \text{malloc}(\dots); (p_{adj} := 0; (S; p))) &= (p := \text{malloc}(\dots); (p_{adj} := 0; (p + (S'; p_{adj})))) \\ &= (p := \text{malloc}(\dots); (p_{adj} := 0; (S'; p) + (S'; p_{adj}))) \\ &= (p := \text{malloc}(\dots); (p_{adj} := 0; (S'; p + p_{adj}))). \end{aligned}$$

This means that by substituting  $S$  with  $S'$  and accessing every pointer using  $p + p_{adj}$  as their address, we access the same memory location. Hence, the program will be semantically equivalent.  $S$  and  $S'$  only contain statements referring to  $p$  or  $p_{adj}$  for simplicity of the proof. Any other statement could be interleaved including control flow statements. By getting all possible execution paths and removing all statements that do not act directly on  $p$ , then we have the same case as  $S$  that can be transformed in  $S'$ .

The proof sketch for the correctness of the pointer assignment transformation can be found in Appendix A.

### 2.3 Technical Implementation

We will now discuss the algorithm that governs our approach. The algorithms are applied to the **AST (abstract syntax tree)** to produce the modified code including the *adjunct* transformation. It is important to note that the whole transformation is source-to-source. The implementation leverages `libclang` to parse the source code. We keep an *adjunctMapping* map that maps pointers to its *adjunct*. As previously mentioned, the type of the *adjunct* variable should be an integer type big enough to address each element of the data-container. We mostly use `int` as it is big enough for most practical purposes, but it could be easily interchanged with bigger or smaller integer types.

For every variable declaration, we check if it is a pointer type. In that case, we append an additional variable declaration for the *adjunct* variable with type `int` and initialize it to 0. We keep a mapping between the pointer variables and their *adjunct*. To avoid name collisions for the *adjunct* variable name, a simple counter and checks are used.

---

```

for all variable declaration of the form type name = init do
  if type is a pointer type then
    adjunctName ← getUniqueName(name + “_adj”)
    adjunctMapping[name] ← adjunctName
    adjunctName init to 0

```

---

We analyze every array subscript expression ( $a[i]$ , where  $a$  is the array expression and  $i$  is the index expression) and verify if the array expression is in the mapping. In case we have a match, we modify the index expression to sum the additional *adjunct* variable. Note that we can handle unary expressions of the type  $*p$  easily by transforming them to  $p[0]$  with a simple transformation (which does not change the semantics as per C standard  $E1[E2]$  is equivalent to  $*(E1 + E2)$ ).

---

```

for all array subscript expression of the form array[index] do
  if array  $\in$  adjunctMapping then
    adjunct  $\leftarrow$  adjunctMapping[array]
    index = index + adjunct

```

---

Finally, we examine every assignment. Here, we have two cases:  $p = p \diamond x$  or  $p = q$ . For both, the left expression must be in the mapping. In the first case ( $p = p \diamond x$ ) the right side must be a binary operation for which the first operator is the same as the left side of the assignment ( $p = q \diamond x$ ,  $p$  and  $q$  must be the same pointer). We then substitute the pointer  $p$  with its *adjunct* ( $p_{\text{adj}} = p_{\text{adj}} \diamond x$ ). In the second case ( $p = q$ ), we check that the right side is also a pointer in the mapping. Then, we append an additional statement that overwrites the *adjunct* of the left side with the *adjunct* of the right ( $p_{\text{adj}} = q_{\text{adj}}$ ).

---

```

for all assignment of the form lhs = rhs do
  if lhs  $\in$  adjunctMapping then
    if rhs is a pointer  $\wedge$  rhs  $\in$  adjunctMapping then
      lhsAdjunct  $\leftarrow$  adjunctMapping[lhs]
      rhsAdjunct  $\leftarrow$  adjunctMapping[rhs]
      lhsAdjunct = rhsAdjunct
    else if rhs == ptr  $\diamond$  expr then
      if lhs == ptr then
        lhsAdjunct  $\leftarrow$  adjunctMapping[lhs]
        lhs = lhsAdjunct
        rhs = lhsAdjunct  $\diamond$  expr

```

---

## 2.4 Previous Approaches

A similar approach was already done specifically for **digital signal processing (DSP)** applications [34]. Their approach could also be extended to general programs and modifies the source code to remove pointer movement. Our biggest innovation is the use of the *adjunct* that enables runtime-determined pointer movements. Previous methods only handled static or compile-time-decidable pointer increments.

For example, the expression:

---

```

if (exp) {
  x = ptr++;
} else {
  y = ptr + 2;
}

```

---

cannot be handled by previous approaches, as it cannot decide at compile time if the pointer must be incremented by 1 or 2. With our *adjunct* approach, it can be handled as the same branch just by modifying the *adjunct* instead of the pointer.

While points-to analysis represents a cutting-edge method widely integrated into modern compilers, its effectiveness in element-sensitive analysis, particularly concerning pointer movements, remains limited. This constraint poses challenges for loop optimization strategies such as vectorization or parallelization, as points-to analysis struggles to grasp element-sensitive aliasing patterns.

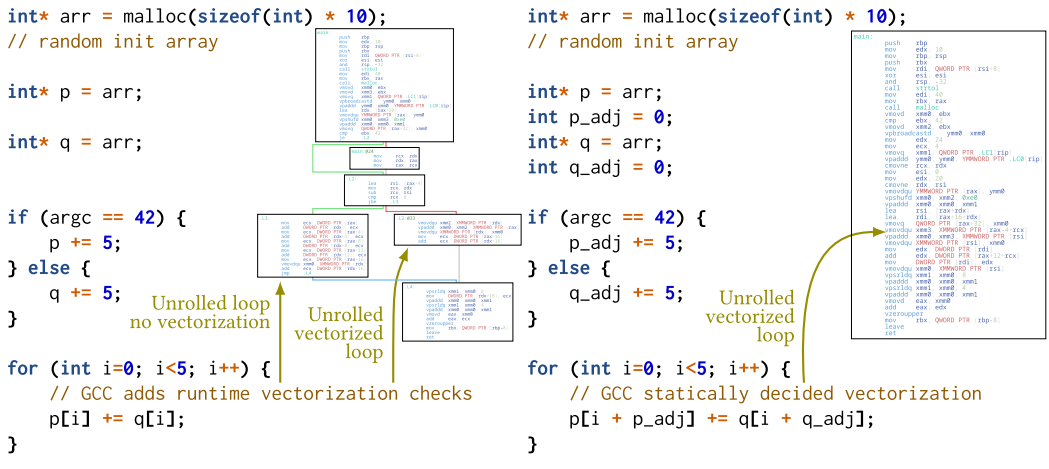


Fig. 5. Left side: example code using pointer movements where the points-to analysis inside GCC is unable to ensure non-aliasing accesses. Right side: code after *adjunct* transformation, where GCC is able to statically decide non-aliasing using points-to analysis and integer analysis. Note the difference in the CFG of the resulting assembly code.

As illustrated in Figure 5, conventional points-to analysis, as implemented in GCC 13, fails to statically discern element-sensitive aliasing in code involving pointer movements. However, following our transformation, GCC successfully identifies the absence of access collisions. It is worth noting that even after the *adjunct* transformation, GCC continues to leverage points-to analysis to recognize the independence between accessed elements. The shown example in Figure 5 includes only a 5-iteration loop to more obviously present the missing vectorization check branch.

Figure 5 illustrates that the transformation is also beneficial for dynamic allocations. In such cases, the base pointer must be stored somewhere to ensure proper memory deallocation. However, even with the base pointer known, the compiler often struggles to fully resolve all aliasing information.

Sui et al. [52] proposed additional analysis techniques for pointer loops, enhancing field-sensitive and element-sensitive methods. However, their work does not address pointer movements, which remain a challenge for compilers, even advanced ones. Our transformation effectively eliminates pointer movements, allowing existing points-to analysis techniques, including advanced element-sensitive approaches, to be applied with greater efficacy. By incorporating points-to analysis with our approach, we enhance the depth of insights and enable advanced code optimization. Our methodology involves modifying the source code, rendering it compatible with various analyzers and optimizers. While our primary focus lies in data-centric frameworks, which often struggle with handling pointers, it is essential to note that our approach is not limited to this domain. The modified source code generated through our method seamlessly integrates with any existing or future frameworks, offering versatility and long-term applicability.

**Scalar Evolution (SCEV)** [10] and other loop analysis methods aim to scrutinize loops for potential optimizations and performance enhancements, including vectorization. However, as demonstrated in numerous examples, current implementations often struggle to identify such opportunities, particularly concerning pointers. Although there have been proposals for improving analysis techniques [14, 33, 39, 52], finding techniques that are both safe and general enough remains challenging. Our transformation addresses this challenge by providing additional information to the compiler, enabling it to leverage existing SCEV techniques for performance improvements. With

better analysis techniques, more patterns can be matched. Importantly, our transformation does not hinder the adoption of new techniques, as the array access pattern is well-established and commonly utilized, making it compatible with existing analyzers. While advanced analyzers may eventually incorporate pointer movements into their analyses, currently, this remains a significant challenge, and most analyzers do not account for it. Hence, we contend that pointer movement continues to pose a problem, and our transformation provides a valuable solution in the current landscape.

## 2.5 Practical Results

*PBKDF2*. To showcase the transformation in practice, we test it on the code snippet from PBKDF2 first presented in Section 1. We expect the inner loop ② to be vectorized by every compiler. What we want to test is whether compilers are able to discover the independence between the iterations of the outer loop ① and the effects that the *adjunct* transformation has on it.

---

<pre style="font-family: monospace; font-size: 0.9em;"> // snippet of the PBKDF2 implementation in OpenSSL // int cplen, n for (int i=0; i&lt;cplen*n; i+=cplen) {   for (int k=0; k&lt;cplen; k++) {     // no loop carried dependence     p[k] = p[k] ^ data[k];   }   // each outer loop iteration works on different   ↪ data   p += cplen; } </pre>	<pre style="font-family: monospace; font-size: 0.9em;"> // adjunct transformed version // int cplen, n for (int i=0; i&lt;cplen*n; i+=cplen) { ①   for (int k=0; k&lt;cplen; k++) {      ②     // data adjunct removed for readability     p[k + p_adj] = p[k + p_adj] ^ data[k];   }   // no pointer movement, the adjunct variable   ↪ is used instead   p_adj += cplen; } </pre>
--	---

---

The code was run both with normal pointer movements (“no *adjunct*”) and with the transformation (“with *adjunct*” variables). It was compiled with different compilers: GCC 12.2.2, Clang 15.0.6, and Polly (same Clang version). We also used the DaCe 0.14.1 data-centric framework to analyze and optimize the code with the resulting file being compiled with GCC. The code was instrumented with PAPI [24] to measure the execution time and the number of instructions. For each test, 10 runs were executed and the median is reported, with the 95% confidence interval being reported. For the number of instructions, the error range is negligible ( $\pm 1,000$  instructions) and not reported. Runs were done with  $n = 100$  and  $cplen = 100 \cdot 10^6$ . As DaCe and Polly produce OpenMP code, we report different values for different thread counts. We compare results with Polly, as it is another compiler that offers automatic parallelization. Note that after the *adjunct* transformation the code only has array accesses, which is a pattern supported by polyhedral compilers.

Figure 6 shows that the adjunct transformation gets a minimal improvement in single-threaded performance. While with multiple threads the data-centric compiler DaCe was able to identify the parallelization opportunity on loop ①, Polly, however, is not able to identify the parallel loop either with or without the *adjunct* transformation. This is the case, because the array-style access of  $p$  is non-affine, as it uses the  $p\_adj$  variable, which is non-affine w.r.t. loop iterators, which is a requirement for the loop to be a SCoP. Polly only acts on SCoPs of programs. Note that as DaCe uses a data-centric IR that utilizes static and scope-defined data containers (for arrays), pointer movements are not supported directly. The *adjunct* transformation is a way to support pointer movements in the data-centric IR without the need to change its inner workings.

The number of instructions (Table 1) neither increase nor decrease with the *adjunct*. As Polly is a collection of transformations on the LLVM-IR that is compiled using Clang, the number of instructions is identical (Polly was not able to find any SCoPs, hence no transformations were

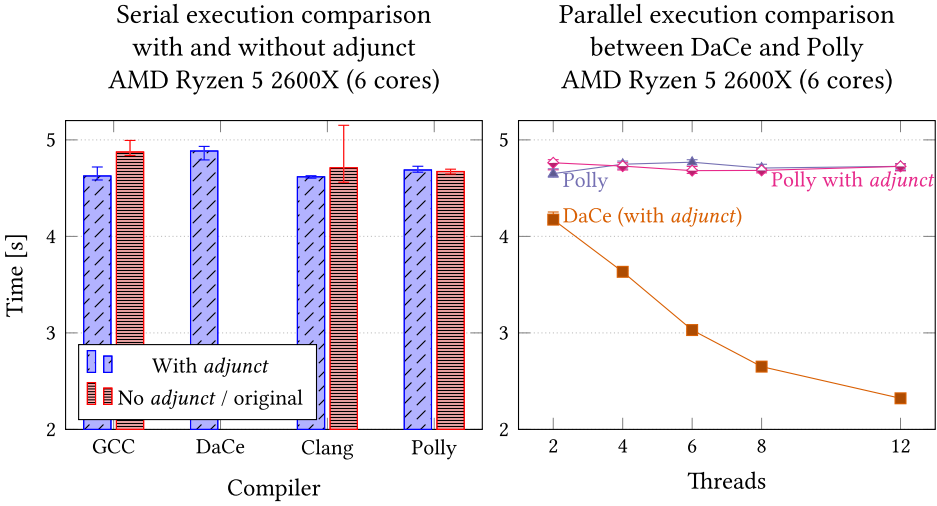


Fig. 6. Serial and parallel runtimes for a simplified code snippet extracted from the PBKDF2 implementation of OpenSSL. Note that DaCe can only analyze the code after using the *adjunct* transformation.

Table 1. Number of Instructions Generated by Different Compilers of the Code Snippet Taken from PBKDF2

Instructions [ $10^6$ ]	No <i>adjunct</i>	With <i>adjunct</i>
GCC	4,380	4,380
Clang	2,974	2,974
Polly	2,974	2,974
DaCe	not supported	4,380

applied). Surprisingly, DaCe has the same number of instructions as GCC. Even if it uses GCC to compile to machine instructions, this is unexpected, as DaCe applies multiple transformations to the code. This can be explained, as even after the transformations, the computation is mostly the same only with additional annotations for parallel execution.

This proves the value of the transformation, but also that the transformation benefits compilers with data-centric IR the most: They can leverage the improved analyzability of pointer movements. Data-centric paradigms otherwise represent pointers as indirection that is challenging—or even impossible—to handle. All compilers see a minimal improvement, but they are less able to capitalize on the improved analyzability.

*LZO (compression algorithms)*. Another instance where pointer movements within loops are prevalent is in compression algorithms. As an illustration, we applied our transformation to the compression function of the **Lempel-Ziv-Oberhumer (LZO)** algorithm [46]. This algorithm is commonly utilized within the Linux Kernel for file-systems and memory, supporting live compression/decompression operations. Notably, it finds applications in BTRFS [1], SquashFS [6], initramfs [3], zram [8], and zswap [9].

Following a similar approach to previous benchmark studies of the LZO algorithm [37], we executed multiple iterations of the algorithm, ensuring each run involved significant computation without increasing memory usage. The compression was performed on a 1 MB file with 2,000 iterations and a block size of 256 KB. As before, we report the median with a 95% confidence

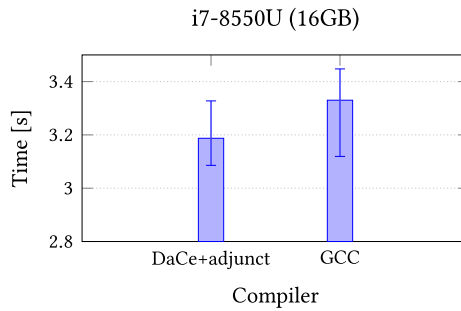


Fig. 7. Serial runtime (single thread) of LZO compression algorithm. Comparison of original implementation compiled with GCC 12.2.2 and DaCe transformed version (including *adjunct* transformation).

interval using the same compiler versions. We compared the original implementation compiled with GCC against DaCe with the adjunct transformation. It is noteworthy that the DaCe code was executed with a single thread, as no significant parallelization opportunities were identified.

Our results (Figure 7) indicate a slight improvement, thanks to the additional vectorization opportunities provided by the transformation. However, achieving more substantial improvements, along with potential parallelization opportunities, proves challenging due to loop-carried dependencies, which would require an algorithm redesign. Nevertheless, in compression algorithms, the adjunct transformation can facilitate modest yet discernible enhancements in runtime performance.

### 3 Limitations

The method we propose can provide compilers with better insights into pointer behavior, but only in certain scenarios. In this section, we go into detail as to the limitations of our approach. The main limitation is about the static decidability of which data container a pointer is pointing to. But, we argue that in those cases an algorithm redesign would be needed for any performance improvement.

The necessity of static decidability arises from the utilization of DaCe as the compiler/framework for optimizations. Although DaCe achieves significant performance improvements, particularly in automatic parallelization, it relies on the ability to statically determine data containers. However, the *adjunct* transformation itself encounters limitations primarily associated with higher-order pointers, as elaborated on in Section 3.2.

Another important aspect to highlight is the utility of our *adjunct* transformation. Simply exposing additional information to the compiler does not guarantee a runtime performance improvement. In earlier examples, we demonstrated how the compiler generates fewer instructions or eliminates branches entirely. Additionally, using DaCe, it created further parallelization opportunities. We discovered that these improvements are predominantly seen in codes where pointers are used as iterators. While this pattern is common in many codebases, as we will discuss in Table 2, no immediate improvements will be offered to codes that do not exhibit this pattern.

#### 3.1 Static Decidability

A first assumption is that a pointer has to always point to a statically decidable data container in any given section of the code. This is required to be able to deterministically identify data accesses. Conditional reassignment introduces uncertainty as to which data container a pointer is pointing to. In such cases, our analysis backs off and does not generate an adjunct. However, unconditional or static pointer re-assignments are supported, as they are not introducing uncertainty as to which data container they point to. We can see two code snippets that show this difference in Figure 8.

## Decidable access - supported

```

int* p;
p = a;
// now p always points to a
p[i] = 5; // accessing a with an offset of i

p = b;
// now p always points to b
p[i] = 2; // accessing b with an offset of i

```

## Undecidable access - not supported

```

int* p;
if (...) { // unknown branch
  p = a;
} else {
  p = b;
}
// p could point to either a or b
p[i] = 5; // undecidable data container

```

Fig. 8. Undecidable vs. decidable pointer accesses.

```
int* a = new int[10];
```

```
int** p = &a;
```

```
int x = (*p)[i] // -> a[i]
a++;
int y = (*p)[i] // -> a[i + 1]
```

```
int* a = new int[10];
int a_adj = 0;
```

```
int** p = &a; ❶
int p_adj = 0;
```

```
int x = (p[p_adj])[i + a_adj] ❷
a_adj++;
int y = (p[p_adj])[i + a_adj] ❸
```

Fig. 9. Example of adjunct transformation with double pointers.

With this assumption, we achieve flawless aliasing detection, as the compiler possesses static knowledge of the data container associated with each pointer. Detecting accesses to the same data simply involves verifying if the data container and indices are identical. Leveraging the *adjunct* transformation streamlines index comparison to a straightforward integer check, often allowing for static analysis if the abstract model is sufficiently precise.

It would be possible to expand the transformation to also support conditional pointers reassignment by creating adjunct versions for each container and replicating the branch decision for each subsequent access. However, this would create unsustainable code and memory replication requirements.

### 3.2 Pointing to Pointers

Double pointers—or higher-order pointers—are supported by applying the transformation recursively, as can be seen in Figure 9. Note that the data container to which *p* is pointing to is statically known. As with simple pointers, we can trace the accesses ❷ and ❸ to container *a* (❶) and get the correct *adjunct* in this case. But the decidability issue remains, as we can see in Figure 10 (left side), where the data container that is accessed is determined by the higher-order pointer location.

The general case could be handled with arrays of *adjunct*, as shown in Figure 10 (right side). However, trying to leverage this approach on general codes would substantially increase the complexity of the code and consume a significant amount of memory. Note that this approach was not implemented because of the unsustainability of the transformation. Therefore, if additional assumptions can be made about the shape of the individual data containers pointed at, then more targeted, efficient approaches can be used, as explained in Section 4.

Although a multidimensional array shares the same memory representation as higher-order pointers, the analysis differs. Our aim is to eliminate pointer movements and replace them with more predictable array accesses. With multidimensional arrays, this pattern is inherent, and our transformation results in code similar to what is typically observed, as pointers are generally

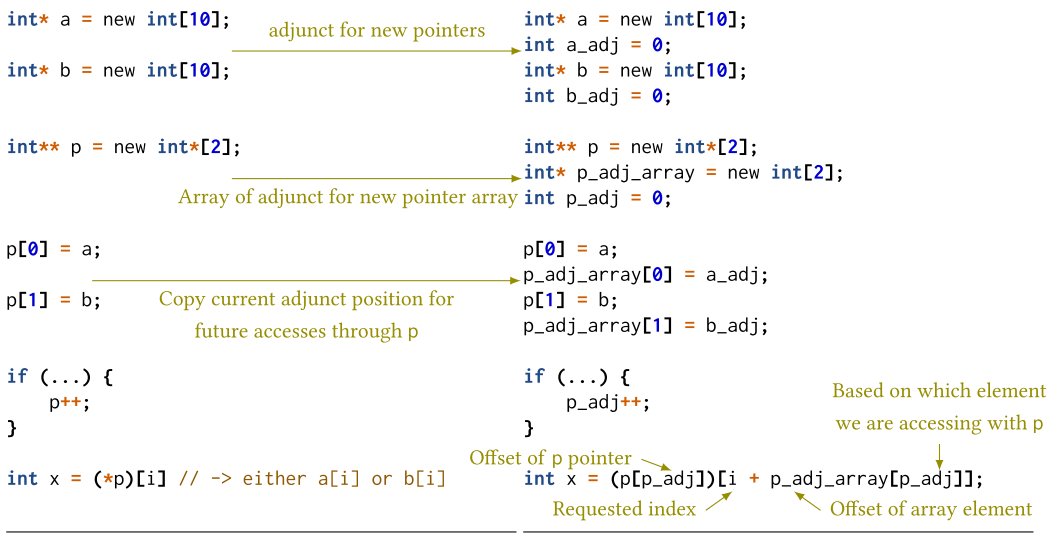


Fig. 10. Example of adjunct transformation with arrays of pointers.

not relocated from multidimensional arrays. Prior proposals have suggested transformations to flatten multidimensional arrays into a single dimension [32]. This approach was also included in GCC between version 4.3 and 4.8. The method is orthogonal to ours and can be applied before or after our transformation, as it will not introduce additional pointer movements.

### 3.3 Evaluating Applicability

In our investigation, we have identified the primary constraint of the *adjunct* transformation: higher-order pointers. The requirement for statically decidable data containers is only a prerequisite of the DaCe framework and not of the *adjunct* transformation itself. To gauge the broader viability of the transformation, we conducted an assessment of its utilization in extensive codebases, specifically focusing on the handling of higher-order pointers.

It is important to clarify our criteria for identifying non-applicable instances. We categorize higher-order pointer usage as constraining only when it potentially involves pointer iteration. Notably, we exempt instances where double pointers are employed to delegate memory allocation responsibilities to another function (refer to Figure 11). Moreover, we exclude considerations of the `argv` parameter in main functions due to its typically diminutive size and minimal involvement in computationally intensive tasks. Our analysis considers application source code, omitting unit tests and examples. Furthermore, our scope is confined to C and C++ files. In the same way, we count single pointers as possible candidates for the *adjunct* transformation.

The outcomes of our investigation are presented in Table 2. Our examination encompassed OpenSSL [5], notable for its cryptographic algorithm implementations, TurboBench [7], which hosts a plethora of compression algorithm implementations, and the Linux kernel [4].

Higher-order pointers are indeed common in these codebases, as expected. However, their frequency is generally several orders of magnitude lower than the total code volume and notably even lower than single order pointer instances. It is essential to note that the provided statistics encompass pointers not exclusively used as iterators. This assessment offers a preliminary insight into the method's broader applicability, highlighting the prevalence of single pointers compared to their higher-order counterparts in programs.

---

```

void init_pointer(char** p, int n) {
    *p = malloc(n);
    memset(*p, 0, n);
}

int main(int argc, char** argv) {
    char* buf;
    init_pointer(&buf, atoi(argv[1]));

    return 0;
}

```

---

Fig. 11. Example usage of double pointers to delegate memory allocation responsibility. This usage is fully supported by the *adjunct* transformation.

Table 2. Number of Lines of Code (LoC), Number of Applicable Instances of the *adjunct* Transformation (#applicable), and Number of Non-applicable Instances (#Non-applicable) in Different Code-bases (Only C and C++)

Code-base	LoC	#applicable	#non-applicable
OpenSSL	704,308	26,925	1,362
TurboBench	854,548	32,680	756
Linux kernel	24,940,479	1,656,065	4,972

#### 4 From Generic to Specific—Refinements for Practical C Codes

We will show how our approach towards improving the analyzability of pointers used as iterators benefits real codes. However, we discovered that for such codes, further refinements are needed such as additional transformations and support for pointers to external calls. All transformations in the following subsections were implemented and are done automatically by the compiler.

##### 4.1 Improving Analyzability by Restructuring Data

As discussed in Section 3, pointing to pointers is a more difficult to analyze scenario, as conditional pointer movements can lead to static undecidability regarding which data container is accessed. However, if additional information is known, then the data structures themselves can be changed to make analysis easier. As this kind of transformation targets a general structure, they do not only target a specific program but the entire set of programs that use that structure.

An example of a structure transformation that we implemented is inside the Mantevo HPCCG benchmark. It uses sparse matrix storage, specifically the **List of Lists (LIL)** format. The matrix is stored using two lists for each row containing the column indices and the non-zero values. The row lists are stored as continuous data, and pointers to them are used to access the correct location based on the current row. In Figure 13, we show the initialization code for a data structure from the HPCCG benchmark (modified for simplicity).

The matrix is accessed using those two lists, as it can be seen in Figure 12 for a matrix-vector multiplication from the same benchmark. With the knowledge that there exists a statically known maximum number of non-zeroes per row, we can transform the list of lists into a matrix, as when the data is accessed (like in 4, we see that the access resembles a 2D array. We transform the initialization of the sparse matrix to utilize a 2D-like structure instead of a contiguous list. The transformation is shown in Figure 13. Thanks to this change, we now have data stored in a more regular pattern (2D array). This enables compilers to apply standard transformations and optimizations on 2D containers.

---

```

for (int i=0; i<nrow; i++) {
    double sum = 0.0; // accumulate sum for each row
    int cur_nnz = A->nnz_in_row[i]; // number of non-zeros per row
    for (int j=0; j<cur_nnz; j++) {
        sum += A->ptr_to_vals[i][j] ❸ // matrix element
            * x[A->ptr_to_inds[i][j]]; // vector element
    }
    y[i] = sum;
}

```

---

Fig. 12. Matrix-vector multiplication with a sparse matrix in LIL format taken from the HPCCG benchmark.

---

<pre> double * curvalptr = new double[max_nnz*nrow]; // do not allocate curvalptr or curindptr int * curindptr = new int[max_nnz*nrow]; for (...) { // for every row     A-&gt;ptr_to_vals[currow] = curvalptr; ❶      A-&gt;ptr_to_inds[currow] = curindptr; ❷      for (...) { // for every value         *curvalptr = 27.0;         *curindptr = curcol;          curvalptr++;         curindptr++;     } } </pre>	<pre> for (...) { // for every row     A-&gt;ptr_to_vals[currow] = new double[max_nnz];     int vals_adj = 0;     A-&gt;ptr_to_inds[currow] = new int[max_nnz];     int inds_adj = 0;     for (...) { // for every value         A-&gt;ptr_to_vals[currow][vals_adj] = 27.0;         A-&gt;ptr_to_inds[currow][inds_adj] = curcol;          vals_adj++;         inds_adj++;     } } </pre>
---	--

---

Fig. 13. Initialization of a sparse matrix in LIL format extracted from the Mantevo HPCCG benchmark. The original code is on the left, while the transformed code is on the right.

The transformation is done first by finding two pointer assignments working on the same struct inside the same scope (❶ and ❷). We use a map to relate the right side of the assignment with the left (curvalptr to A->ptr\_to\_vals[currow]). We then create an *adjunct* and transform the code in a similar way to the general pointer transformation. Using the previously created map, we find all pointer accesses that must be transformed and substitute them with array access using the *adjunct*. In the same way, we find pointer arithmetic operations and substitute the pointer with the *adjunct*.

The benefit of using such specific pattern-based transformations is that they can be used in conjunction with our general algorithm and therefore be integrated into the same workflow. This creates the possibility to efficiently handle a wide range of other access patterns without the need for separate workflows or manual code modification.

It is important to note that for multidimensional arrays, allocating a continuous buffer and then splitting it by storing pointers introduces uncertainty for static analysis, as explained in Section 3.2. Such patterns are unsupported by our current method. However, our LIL transformation automatically converts this pattern into a 2D array. In other scenarios, implementing additional transformations may be necessary to align with the limitations of our method.

## 4.2 Handling External Calls with Pointer Arguments

Some parts of a program, such as external library calls, are outside the scope of static compiler analysis. These must therefore be considered black boxes. A common pattern in C when calling external functions is to use pointers as arguments for inputs and outputs. One such example is the memcopy function from the C standard library. The function with the following signature:

---

```
void* memcpy(void* destination, const void* source, size_t num);
```

---

takes two pointers and an integer num and copies num bytes from the source pointer to the destination.

In the previous section, we discussed the possible modifications and movement of pointers and their impact on decidability. In the example of `memcpy`, pointers are not modified. In C, arguments are passed by copy and not by reference, therefore callee modifications of arguments are not propagated to the caller. The same argument applies to pointers. What is modified in those cases is the content of the pointer, hence the elements of the data container that the pointer is pointing to. A function taking a pointer as an argument can modify its contents. This poses a challenge, as data dependencies can no longer be tracked. In Figure 14, we use `memcpy` instead of a simple assignment.

On the left side of the figure, the data in `p` depends on the value previously written to it by `memcpy` (dependency shown by the dashed arrow). This enforces that the loop must be executed in order. If we remove this dependency (dashed arrow), then loop iterations would be independent. This would permit the compiler to vectorize the loop producing the incorrect result.

We previously assumed that the second argument of `memcpy` is only read, but this is an insight gained by looking at the implementation of `memcpy` and not black-box analysis. Without outside information, no compiler framework can overcome this issue. In the right side of Figure 14, `q` is only read from, but the compiler cannot infer this. This creates a spurious data dependency between iterations and prevents the loop from being parallelized.

While it is good practice to make pointer arguments that are read-only `const`, not every function or library does so. Our solution is to use whitelists for often-used library calls—manually annotating library functions to specify if a pointer is write-only, read-write, or read-only. This whitelist could become a database of known functions that could even be automatically populated through compiler analysis, as it only needs to be performed once for any given library implementation. Annotations only provide information about which data container was read or written. We, therefore, assume conservatively that the entire data container could be read or written.

### 4.3 Stateful External Calls

Some libraries store an internal state that is opaque to the program calling functions provided by the library—great examples being MPI or OpenGL. One such library is a part of OpenSSL, namely, **HMAC (Hash Message Authentication Code)**—it uses an internal state to store hashes and keys between calls. This data is saved in an internal data structure and a pointer to it is provided to calling functions. This pointer (called context in this implementation) is never modified by the user code, but only by library calls.

---

```
HMAC_CTX *hctx = HMAC_CTX_new(); ❶
for (...) {
    HMAC_CTX_copy(hctx, base_hctx); ❷
    // do operations with hctx
}
HMAC_CTX_free(hctx);
```

---

In the example above, without any additional information, it appears that the `hctx` pointer is initialized outside the loop (❶) and that the call to `HMAC_CTX_copy` within the loop (❷) could read and write to `hctx`. This creates a data dependency between loop iterations. In reality, `HMAC_CTX_copy` does not read the data of the first argument (`hctx`)—that value is only written to and effectively used as a local variable within the scope of the loop. Therefore, by marking

---

```

char* p = new char[1];
*p = 0;
for (int i=0; i<n; i++) {
  char q = *p + i; // use *p from previous
  ↪ iteration
  memcpy(p, &q, 1); // equal to *p = q
}

```

---

```

int* q = new char[1];
*q = 42;
for (int i=0; i<n; i++) {
  char p = 0;
  memcpy(&p, q, 1); // equal to p = *q
  data[i] = p + i; // data[i] = 42 + i;
}

```

---

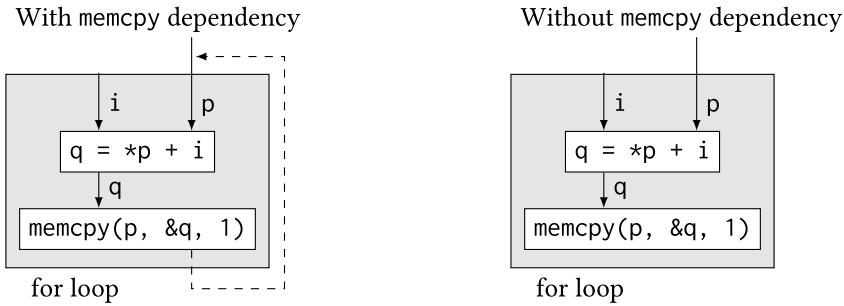


Fig. 14. Left side: memcpy creates a dependency between loop iterations. Right side: p is a loop local variable and memcpy is used to assign values to it.

the dependency on (hctx) in HMAC\_CTX\_copy as write-only and noticing that it is never used afterwards, the loop can be parallelized. This approach essentially performs an escape analysis [41], identifying that the variable within the loop does not escape the thread executing each iteration.

## 5 Evaluation

To evaluate our transformation, we extended the DaCe [15, 20] pipeline by adding the pointer disaggregation transformation explained in Section 2 and the specific transformations explained in Section 4. The approach described in Section 4.2 and Section 4.3 is implemented by adding a whitelist of additional dependencies in the data-centric IR (**intermediate representation**) used by DaCe.

As detailed and demonstrated in Section 2.5, while incremental performance enhancements are attainable across various compilers, the constrained scope of vectorization inhibits substantial performance gains. Consequently, we prioritize automatic parallelization compilers such as Polly and DaCe, which hold promise in uncovering novel opportunities facilitated by the transformations implemented. Specifically, we direct our attention to DaCe due to its inherent data-centric approach, which offers superior analysis of data dependencies.

We measured performance on a dual-socket 2×6 core (2×12 threads) Intel Xeon X5670 @ 2.93 GHz with 48 GB of RAM. We compare the DaCe data-centric framework (using GCC 12.1.1 as a backend compiler) against GCC and Polly (using Clang 15.0.6). We report the median of 10 runs with a confidence interval of 95%. OpenMP is used for parallel execution. Integrating the *adjunct* transformation into Polly did not reveal any additional SCoPs, and consequently, no further parallelization opportunities were identified. Hence, we provide the runtime results of Polly without the *adjunct* transformation. We specifically chose to compare with Polly due to its widespread availability as part of the LLVM/Clang suite, offering some level of automatic parallelization capabilities. Our evaluation was conducted on the Mantevo HPCCG benchmark and the OpenSSL PBKDF2 implementation, with the results presented below.

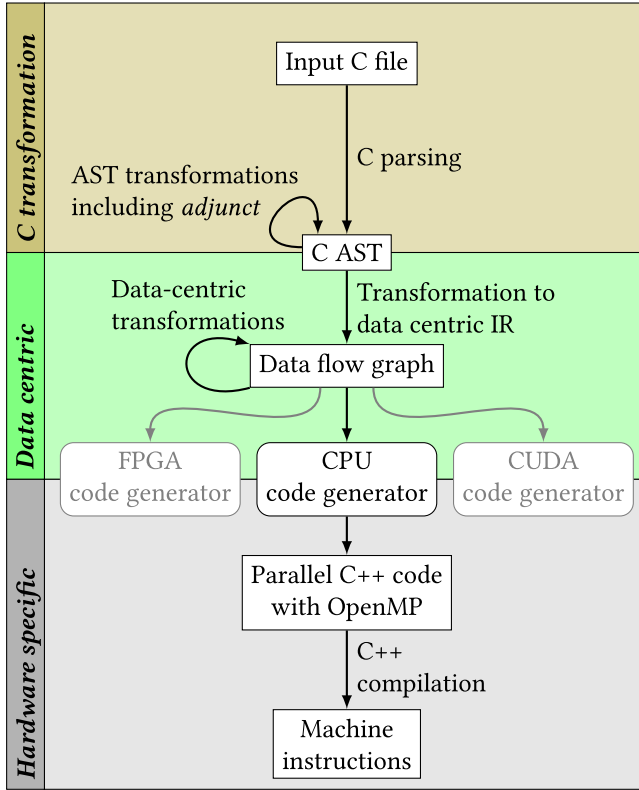


Fig. 15. Workflow for C program optimization including *adjunct* transformation and leveraging the DaCe data-centric framework.

### 5.1 OpenSSL PBKDF2

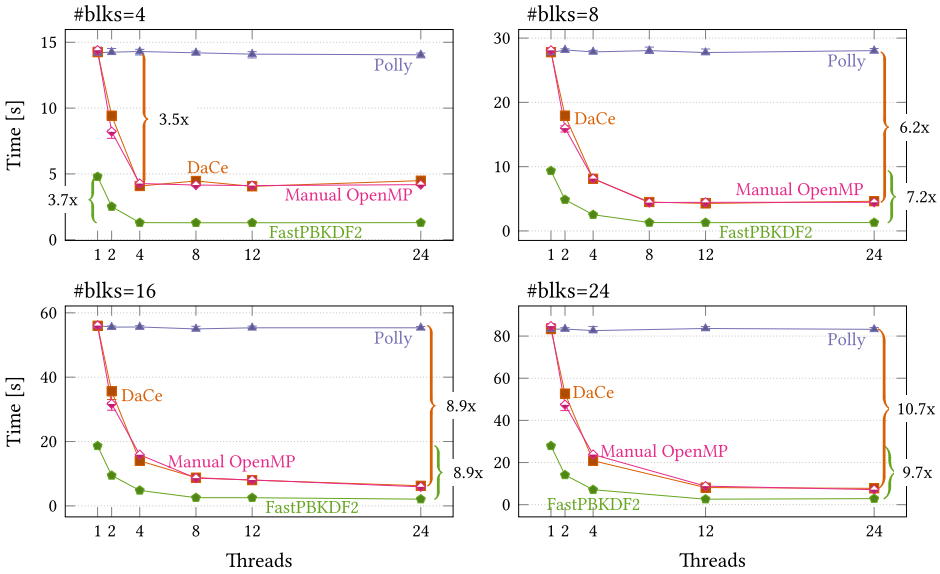
The **Password Based Key Derivation Function 2 (PBKDF2)** is a derivation function that derives a cryptographically secure key from a password. PBKDF2 applies a **Hash-based Message Authentication Code (HMAC)** function multiple times to a provided password and salt. Based on the required length of the key, this process is repeated multiple times. A summary of the process is provided in Figure 16. We can notice that each single  $B_i$  blocks can be computed independently of any other.

The implementation inside OpenSSL does not include parallel options. We applied our pipeline to the OpenSSL code to auto-parallelize the code. We compare the runtime against Polly and a manually parallel version that was written using the OpenSSL implementation as a starting point. Only the PBKDF2 algorithm was analyzed, all HMAC calls are treated as external calls and use the standard OpenSSL implementation. For completeness, we compare it with FastPBKDF2 [17], an implementation of the same algorithm that has been developed for parallelism from the ground up. We used SHA1 as the HMAC function,  $5 \cdot 10^6$  iterations, and an output key size of 480 bytes (or 24 blocks), and we summarize our results in Figure 17.

We then varied the problem size, represented by the number of blocks. The results (Figure 17) show a consistent trend across all experiments. Our approach was able to obtain comparable results to the manually parallelized version, providing at most a  $10.7\times$  improvement with 24 threads. Polly was not able to identify any parallel opportunities due to the challenges of analyzing

$$\begin{aligned}
 key &= \text{PBKDF2}(\text{HMAC}, \text{password}, \text{salt}, \text{iterations}, \text{keyLen}) \\
 &= B_0 \text{ ++ } B_1 \text{ ++ } \dots \text{ ++ } B_{\text{keyLen}/\text{hlen}} \\
 B_i &= U_0^i \oplus U_1^i \oplus \dots \oplus U_{\text{iterations}}^i \\
 U_0^i &= \text{HMAC}(\text{password}, \text{salt} + i) \\
 U_1^i &= \text{HMAC}(\text{password}, U_0^i) \\
 &\vdots \\
 U_{\text{iterations}}^i &= \text{HMAC}(\text{Password}, U_{\text{iterations}-1}^i)
 \end{aligned}$$

Fig. 16. PBKDF2 scheme. In this representation, ++ is the string concatenation, ⊕ is the XOR operator, and hlen is the output length of the HMAC function.



PBKDF2 with various block sizes

Fig. 17. Runtime of various parallelized PBKDF2 implementations using different block counts (block count determines the problem size) and using multiple thread counts. Increasing the thread count beyond the number of blocks would be ineffective, as the work could not be meaningfully divided among threads.

pointers. The FastPBKDF2 implementation is considerably faster than any OpenSSL equivalent, mainly due to the serial runtime of FastPBKDF2 version being three times faster: 27.7 s versus 84.5 s for OpenSSL. This reinforces the idea that tools can provide significant performance increases and find opportunities for parallelism, but nothing surpasses finding a better algorithm altogether.

### 5.2 Mantevo HPCCG

The Mantevo HPCCG benchmark computes the conjugate gradient on a sparse matrix. The sparse matrix is stored using the LIL format. We leverage the specific transformation explained in Section 4.1 to improve analyzability. The LIL transformation is applied once only to the input file

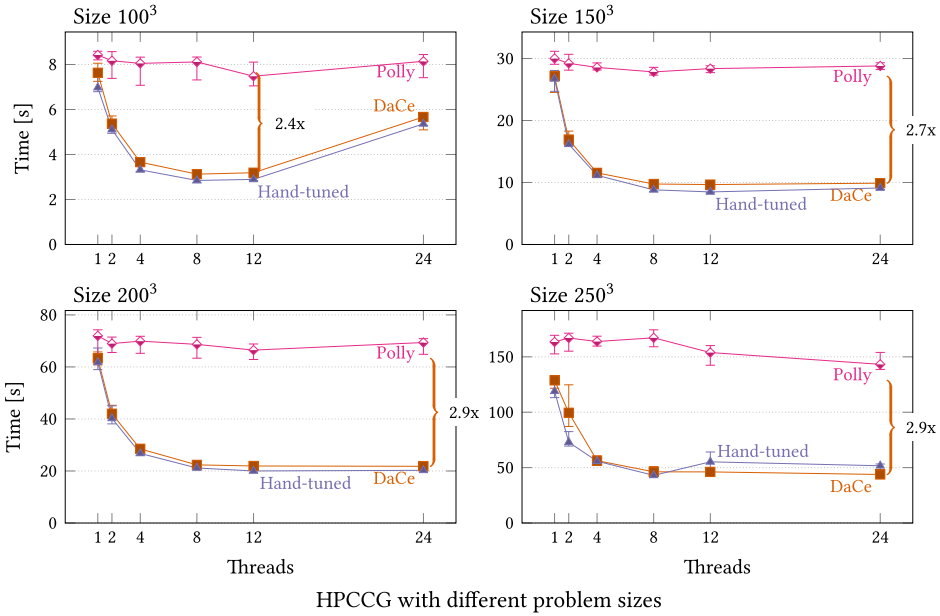


Fig. 18. Runtime of Mantevo HPCCG benchmark with different compilers.

for DaCe. We compare our pipeline against Polly with the same preprocessed input. The baseline is obtained using the original benchmark with OpenMP enabled.

We can see that Polly was not able to find parallel opportunities, as pointers are used to access the sparse matrix. Our approach was able to parallelize all five loops. The performance of our automatically parallelized code matches the hand-tuned version developers created across all experiments. At larger problem sizes, our approach even outperforms the reference implementation by up to 18%.

### 5.3 Lempel–Ziv–Oberhumer Compression Algorithm

In Section 2.5, we presented results from a benchmark on the LZO compression algorithm. Although automatic parallelization was not achieved, there was still a modest enhancement in single-threaded performance. Achieving effective automatic parallelization would necessitate an algorithm redesign due to the presence of loop-carried dependencies. However, our method managed to achieve a 4% runtime enhancement without requiring any algorithm rewriting. Given the analogous pointer movement patterns observed in most compression algorithms, we anticipate similar, if not superior, outcomes by extending our pipeline to encompass them as well.

## 6 Related Work

*Pointer analysis in C.* Pointer analysis has been a topic of research for decades. One of the most impactful approaches, the “points-to” analysis, was proposed by Andersen et al. [11] and developed and improved over the years [19, 25, 38]. Our approach is orthogonal to this method, and while more constrained in the patterns it detects, it provides a powerful benefit towards automatic parallelism detection.

*Parallelization of C programs.* Numerous approaches are emerging to identify parallelism in C code, with varying levels of automation. Tools like DiscoPoP [55] detect loops that can be parallelized with OpenMP, while frameworks such as Polly [31] and Pluto [18] use polyhedral models to

generate parallel code automatically. However, these methods struggle with codes that use pointers as iterators. Our approach, as demonstrated with DaCe, could be integrated into these workflows to extend their capabilities.

*Parallelization of programs with pointers.* Utilizing the **Distributed Dynamic Pascal (DDP)** language [34] facilitates the development of parallel programs involving pointers. The DDP language introduces explicit pointer access mechanisms to enable the parallelization of pointer-related operations. In contrast, our approach seamlessly integrates with existing C programs, obviating the necessity for transpilation processes.

*Intermediate representations.* The LLVM IR [42] allows for many transformations and code optimizations. However, tracking pointer dependencies across scopes remains difficult. A new opportunity has appeared with the recent rise of MLIR [43], a framework that allows multiple IR dialects to co-exist and their different strengths to all contribute to overall code analyzability and performance. The MemRefType built-in dialect already enables to specify the shape of the underlying data. This includes the option to save the start of a data container even if the pointer is moved. MLIR would permit our approach to be implemented as a dialect, bringing it to the wider LLVM ecosystem.

*Source code modification.* The alteration of source code within DSP programs facilitates the elimination of pointer references as outlined in the work by Franke et al. [26]. While the approach bears some resemblance to our proposed method, it exhibits comparatively reduced flexibility. It exclusively encompasses static code modifications, devoid of the incorporation of the *adjunct* concept, which enables the utilization of compile-time-determined values exclusively. The primary aim remains the enhancement of computational efficiency, albeit without resorting to parallel processing techniques.

*Pointers metadata.* Incorporating metadata into pointers is not a novel concept, as evidenced by previous studies [51, 54]. In other scenarios, where the emphasis is on safety rather than performance, statically known mappings to pointers have been established. This facilitates the addition of runtime bounds checking, analogous to how we introduce runtime pointer movements through source code modifications.

*Stream Semantic Registers.* **Stream Semantic Registers (SSR)** [50] is a RISC-V ISA extension that offloads memory access management to hardware and automatically advances addresses in loops. However, SSR relies on known and regularly strided memory locations, which is not always true for pointers. Our transformation overcomes this limitation by converting pointers into array-style accesses, making SSR applicable.

## 7 Conclusion

In this work, we introduce a static transformation that separates the use of pointers as handles to data containers from their use as iterators. This improves code analyzability and data-centric compilers are shown to benefit from this transformation as eliminating indirection exposes additional parallelization opportunities. Using our approach on the Mantevo HPCCG benchmark, we were able to match the developer-optimized version and even surpass it by up to 6%. On the OpenSSL PBKDF2 implementation, we were able to automatically parallelize it and obtain up to an 11× speedup.

## Appendix

### A Proof Sketch of Pointer Assignment

We want to show that the assignment of pointers gives equivalent results after the application of the *adjunct* transformation described in Figure 4. To do so, we introduce a new pointer  $q$  with its

$q_{adj}$ . Let  $n, m$  be arbitrary integers, then we define  $X, Y$  and  $X', Y'$  as

$$\begin{aligned} X &= (p := p + x_i | x_i \in \mathbb{Z}, 0 \leq i < n) \\ Y &= (v^i := v^i + x_i | x_i \in \mathbb{Z} \ \& \ v^i \in \{p, q\}, n \leq i < m) \\ X' &= (p_{adj} := p_{adj} + x_i | x_i \in \mathbb{Z}, 0 \leq i < n) \\ Y' &= (v_{adj}^i := v_{adj}^i + x_i | x_i \in \mathbb{Z} \ \& \ v_{adj}^i \in \{p_{adj}, q_{adj}\}, n \leq i < m). \end{aligned}$$

Using  $;$  to concatenate commands, we define  $S$  with

$$S = (X; (q := p; Y)),$$

where it represents the execution of an arbitrary number of pointer movement statements followed by a pointer assignment and another arbitrary number of pointer movement statements. In the same way, we define  $S'$  as the *adjunct* transformation of  $S$ .

$$S' = (X'; (q := p; (q_{adj} := p_{adj}; Y')))$$

Note that the  $;$  operator is right associative. Then, we define  $Y'_q$  as

$$Y'_q = \sum_{i=n | v_{adj}^i = q_{adj}}^m x_i,$$

i.e., the difference of value after executing  $Y'$  on  $q_{adj}$ . Then,  $(Y'; q_{adj}) = q_{adj} + Y'_q$ . Note that  $X$  and  $X'$  only act on  $p$  and  $p_{adj}$ , respectively. This is to have a simpler proof, but it can be easily shown that by defining  $X$  and  $X'$  in a similar way as  $Y$  and  $Y'$ , the same result will be obtained.

For the sake of a shorter syntax and more readable proof, we omit the declaration of the pointers and *adjunct* integer variables. i.e.,

$$(p := \text{malloc}(\dots); (p_{adj} := 0; (q := \text{malloc}(\dots); (q_{adj} := 0; (S; q))))),$$

as it will be carried without modifications through all the proof steps. Then, we can derive

$$\begin{aligned} S; q &= X; (q := p; (Y; q)) \\ (\text{adjunct transformation}) &= X; (q := p; (q + (Y'; q_{adj}))) \\ (\text{distributive}) &= X; ((q := p; q) + (q := p; (Y'; q_{adj}))) \\ (\text{no effect statement}) &= X; ((q := p; q) + (Y'; q_{adj})) \\ (\text{assignment}) &= X; (p + (Y'; q_{adj})) \\ (\text{distributive}) &= (X; p) + (X; (Y'; q_{adj})) \\ (\text{adjunct transformation}) &= ((X'; p) + (X'; p_{adj})) + (X; (Y'; q_{adj})) \\ (\text{no effect statement}) &= p + (X'; p_{adj}) + (X; (Y'; q_{adj})) \\ (\text{no effect statement}) &= p + (X'; p_{adj}) + (Y'; q_{adj}) \\ (\text{sum expansion of adjunct}) &= p + (X'; p_{adj}) + q_{adj} + Y'_q \\ (\text{adjunct value of 0}) &= p + (X'; p_{adj}) + Y'_q \\ (\text{no effect statement}) &= p + (X'; p_{adj}) + (X'; Y'_q) \\ (\text{distributive}) &= p + (X'; (p_{adj} + Y'_q)) \\ (\text{no effect statement}) &= p + (X'; (q := p; (p_{adj} + Y'_q))) \\ (\text{assignment}) &= p + (X'; (q := p; (q_{adj} := p_{adj}; q_{adj} + Y'_q))) \end{aligned}$$

$$\begin{aligned}
(Y'_q \text{ definition}) &= p + (X'; (q := p; (q_{adj} := p_{adj}; (Y'; q_{adj}))) \\
(S' \text{ definition}) &= p + (S'; q_{adj}) \\
(\text{no effect statement}) &= (X'; p) + (S'; q_{adj}) \\
(\text{assignment}) &= (X'; (q := p; q)) + (S'; q_{adj}) \\
(\text{no effect statement}) &= (X'; (q := p; (q_{adj} := p_{adj}; q))) + (S'; q_{adj}) \\
(\text{no effect statement}) &= (X'; (q := p; (q_{adj} := p_{adj}; (Y'; q)))) + (S'; q_{adj}) \\
(S' \text{ definition}) &= (S'; q) + (S'; q_{adj}) = q + (S'; q_{adj}).
\end{aligned}$$

Now, we have proven the equivalence of the pointer assignment transformation stated in Figure 4.

## References

- [1] [n. d.]. BTRFS compression documentation. Retrieved from <https://btrfs.readthedocs.io/en/latest/Compression.html>
- [2] [n. d.]. Intel® C++ Compiler Classic Developer Guide and Reference. Retrieved from <https://www.intel.com/content/www/us/en/docs/cpp-compiler/developer-guide-reference/2021-8/vectorization-programming-guidelines.html>
- [3] [n. d.]. lib, initramfs: Add initramfs LZO compression. Retrieved from <https://lore.kernel.org/all/1238593252-3435-1-git-send-email-andr345@gmail.com/>
- [4] [n. d.]. Linux kernel repository. Retrieved from <https://github.com/torvalds/linux>
- [5] [n. d.]. OpenSSL repository. Retrieved from <https://github.com/openssl/openssl>
- [6] [n. d.]. Squashfs documentation. Retrieved from <https://dr-emann.github.io/squashfs/squashfs.html>
- [7] [n. d.]. TurboBench repository. Retrieved from <https://github.com/powturbo/TurboBench>
- [8] [n. d.]. zram documentation. Retrieved from <https://www.kernel.org/doc/html/next/admin-guide/blockdev/zram.html>
- [9] [n. d.]. zswap documentation. Retrieved from <https://www.kernel.org/doc/html/v4.18/vm/zswap.html>
- [10] Javed Absar. 2018. Scalar evolution-demystified. In *European LLVM Developers Meeting*.
- [11] L. O. Andersen and Københavns Universitet. Datalogisk Institut. 1994. *Program Analysis and Specialization for the C Programming Language*. Datalogisk Institut, Københavns Universitet. Retrieved from <https://books.google.ch/books?id=3pD1GwAACAAJ>
- [12] Krste Asanović, Ras Bodik, Bryan Christopher Catanzaro, Joseph James Gebis, Parry Husbands, Kurt Keutzer, David A. Patterson, William Lester Plishker, John Shalf, Samuel Webb Williams, and Katherine A. Yelick. 2006. The landscape of parallel computing research: A view from berkeley. Retrieved from <http://www2.eecs.berkeley.edu/Pubs/TechRpts/2006/EECS-2006-183.html>
- [13] Gordon Bell. 1994. Scalable, parallel computers: Alternatives, issues, and challenges. *Int. J. Parallel Program.* 22, 1 (1994), 3–46.
- [14] M. A. Belyaev, M. Akhin, and V. M. Itsykson. 2014. Improving static analysis by loop unrolling on an arbitrary iteration. *Univ. Scient. J.* 8 (2014), 154–168.
- [15] Tal Ben-Nun, Johannes de Fine Licht, Alexandros Nikolaos Ziogas, Timo Schneider, and Torsten Hoefler. 2019. Stateful dataflow multigraphs: A data-centric model for performance portability on heterogeneous architectures. In *International Conference for High Performance Computing, Networking, Storage and Analysis (SC'19)*.
- [16] M. D. Beynon, H. Andrade, and J. Saltz. 2002. Low-cost non-intrusive debugging strategies for distributed parallel programs. In *IEEE International Conference on Cluster Computing*. 439–442. DOI : <https://doi.org/10.1109/CLUSTER.2002.1137778>
- [17] Joseph Birr-Pixton. 2015. PBKDF2: performance matters. Retrieved from <https://jbp.io/2015/08/11/pbkdf2-performance-matters.html>
- [18] Uday Bondhugula, Muthu Baskaran, Sriram Krishnamoorthy, J. Ramanujam, Atanas Rountev, and P. Sadayappan. 2008. Automatic transformations for communication-minimized parallelization and locality optimization in the polyhedral model. In *Compiler Construction*, Laurie Hendren (Ed.). Springer Berlin, 132–146.
- [19] Martin Bravenboer and Yannis Smaragdakis. 2009. Strictly declarative specification of sophisticated points-to analyses. In *24th ACM SIGPLAN Conference on Object Oriented Programming Systems Languages and Applications (OOPSLA'09)*. Association for Computing Machinery, New York, NY, USA, 243–262. DOI : <https://doi.org/10.1145/1640089.1640108>
- [20] Alexandru Calotiu, Tal Ben-Nun, Grzegorz Kwasniewski, Johannes de Fine Licht, Timo Schneider, Philipp Schaad, and Torsten Hoefler. 2022. Lifting C semantics for dataflow optimization. In *36th ACM International Conference on*

- Supercomputing (ICS'22)*. Association for Computing Machinery, New York, NY, USA, Article 17, 13 pages. DOI : <https://doi.org/10.1145/3524059.3532389>
- [21] Stephen Cass. 2018. Chip Hall of Fame: Intel 4004 Microprocessor. Retrieved from <https://spectrum.ieee.org/chip-hall-of-fame-intel-4004-microprocessor>
- [22] Jong-Deok Choi, Barton P. Miller, and Robert H. B. Netzer. 1991. Techniques for debugging parallel programs with flowback analysis. *ACM Trans. Program. Lang. Syst.* 13, 4 (Oct. 1991), 491–530. DOI : <https://doi.org/10.1145/115372.115324>
- [23] L. Dagum and R. Menon. 1998. OpenMP: An industry standard API for shared-memory programming. *IEEE Comput. Sci. Eng.* 5, 1 (1998), 46–55. DOI : <https://doi.org/10.1109/99.660313>
- [24] Anthony Danalis, Heike Jagode, and Jack Dongarra. 2018. PAPI: Counting outside the Box. 8th JLESC Meeting, Barcelona, Spain.
- [25] Maryam Emami, Rakesh Ghiya, and Laurie J. Hendren. 1994. Context-sensitive interprocedural points-to analysis in the presence of function pointers. In *ACM SIGPLAN Conference on Programming Language Design and Implementation (PLDI'94)*. Association for Computing Machinery, New York, NY, USA, 242–256. DOI : <https://doi.org/10.1145/178243.178264>
- [26] Björn Franke and Michael O'Boyle. 2001. Compiler transformation of pointers to explicit array accesses in DSP applications. In *Compiler Construction*, Reinhard Wilhelm (Ed.). Springer Berlin, 69–85.
- [27] Roy Frostig, Matthew Johnson, and Chris Leary. 2018. Compiling machine learning programs via high-level tracing. Retrieved from <https://mlsys.org/Conferences/doc/2018/146.pdf>
- [28] Fabrizio Gagliardi, Miquel Moreto, Mauro Olivieri, and Mateo Valero. 2019. The international race towards exascale in Europe. *CCF Trans. High Perform. Comput.* 1, 1 (2019), 3–13.
- [29] GitHub. 2022. GitHub API, repository count. Retrieved from <https://api.github.com/search/repositories?q=language:Ccreated:<=2022-12-31>
- [30] GitHub. 2022. GitHub Top Programming Languages. Retrieved from <https://octoverse.github.com/2022/top-programming-languages>
- [31] Tobias Grosser, Armin Groesslinger, and Christian Lengauer. 2012. Polly –Performing polyhedral optimizations on a low-level intermediate representation. *Parallel Process. Lett.* 22, 04 (2012), 1250010. DOI : <https://doi.org/10.1142/S0129626412500107>
- [32] Tobias Grosser, J. Ramanujam, Louis-Noel Pouchet, P. Sadayappan, and Sebastian Pop. 2015. Optimistic delinearization of parametrically sized arrays. In *29th ACM on International Conference on Supercomputing (ICS'15)*. Association for Computing Machinery, New York, NY, USA, 351–360. DOI : <https://doi.org/10.1145/2751205.2751248>
- [33] Richard Günther. 2006. Profile driven loop transformations. In *GCC Developers' Summit*. Citeseer, 49.
- [34] R. Gupta. 1992. SPMD execution of programs with dynamic data structures on distributed memory machines. In *International Conference on Computer Languages*. 232–241. DOI : <https://doi.org/10.1109/ICCL.1992.185487>
- [35] ISO. 1999. *ISO C Standard 1999*. Technical Report. Retrieved from <http://www.open-std.org/jtc1/sc22/wg14/www/docs/n1124.pdf> Subsection 6.5.2 Postfix operators.
- [36] Andrei Ivanov, Nikoli Dryden, Tal Ben-Nun, Shigang Li, and Torsten Hoefler. 2020. Data Movement Is All You Need: A Case Study on Optimizing Transformers. DOI : <https://doi.org/10.48550/ARXIV.2007.00072>
- [37] Jason Kane and Qing Yang. 2012. Compression speed enhancements to LZ0 for multi-core systems. In *IEEE 24th International Symposium on Computer Architecture and High Performance Computing*. 108–115. DOI : <https://doi.org/10.1109/SBAC-PAD.2012.29>
- [38] George Kastrinis and Yannis Smaragdakis. 2013. Hybrid context-sensitivity for points-to analysis. In *34th ACM SIGPLAN Conference on Programming Language Design and Implementation (PLDI'13)*. Association for Computing Machinery, New York, NY, USA, 423–434. DOI : <https://doi.org/10.1145/2491956.2462191>
- [39] Yeonsoo Kim, Shinhyung Yang, Shin-Dug Kim, and Bernd Burgstaller. 2019. Code optimizations for in-network processing: The state of scalar evolution in LLVM: The state of scalar evolution in LLVM. *Proc. Korea Telecommun. Societ.* 2019.1 (2019), 434–437.
- [40] Maria Kotsifakou, Prakash Srivastava, Matthew D. Sinclair, Rakesh Komuravelli, Vikram Adve, and Sarita Adve. 2018. HPVM: Heterogeneous parallel virtual machine. In *23rd ACM SIGPLAN Symposium on Principles and Practice of Parallel Programming (PPoPP'18)*. Association for Computing Machinery, New York, NY, USA, 68–80. DOI : <https://doi.org/10.1145/3178487.3178493>
- [41] Thomas Kotzmann and Hanspeter Mössenböck. 2005. Escape analysis in the context of dynamic compilation and deoptimization. In *1st ACM/USENIX International Conference on Virtual Execution Environments (VEE'05)*. Association for Computing Machinery, New York, NY, USA, 111–120. DOI : <https://doi.org/10.1145/1064979.1064996>
- [42] C. Lattner and V. Adve. 2004. LLVM: A compilation framework for lifelong program analysis & transformation. In *International Symposium on Code Generation and Optimization (CGO'04)*. 75–86. DOI : <https://doi.org/10.1109/CGO.2004.1281665>

- [43] Chris Lattner, Mehdi Amini, Uday Bondhugula, Albert Cohen, Andy Davis, Jacques Pienaar, River Riddle, Tatiana Shpeisman, Nicolas Vasilache, and Oleksandr Zinenko. 2020. MLIR: A Compiler Infrastructure for the End of Moore’s Law. arXiv:2002.11054 [cs.PL]
- [44] Message Passing Interface Forum. 2021. *MPI: A Message-Passing Interface Standard Version 4.0*. Retrieved from <https://www.mpi-forum.org/docs/mpi-4.0/mpi40-report.pdf>
- [45] Gordon E. Moore. 2006. Cramming more components onto integrated circuits, reprinted from electronics, volume 38, number 8, april 19, 1965, pp.114 ff. *IEEE Solid-State Circ. Societ. Newslett.* 11, 3 (2006), 33–35. DOI : <https://doi.org/10.1109/N-SSC.2006.4785860>
- [46] Markus F. X. J. Oberhumer. 2017. Lempel–Ziv–Oberhumer. Retrieved from <https://www.oberhumer.com/opensource/lzo/>
- [47] Geraldo F. Oliveira, Juan Gómez-Luna, Lois Orosa, Saugata Ghose, Nandita Vijaykumar, Ivan Fernandez, Mohammad Sadrosadati, and Onur Mutlu. 2021. DAMOV: A new methodology and benchmark suite for evaluating data movement bottlenecks. *IEEE Access* 9 (2021), 134457–134502. DOI : <https://doi.org/10.1109/ACCESS.2021.3110993>
- [48] Jonathan Ragan-Kelley, Andrew Adams, Dillon Sharlet, Connelly Barnes, Sylvain Paris, Marc Levoy, Saman Amarasinghe, and Frédo Durand. 2017. Halide: Decoupling algorithms from schedules for high-performance image processing. *Commun. ACM* 61, 1 (Dec. 2017), 106–115. DOI : <https://doi.org/10.1145/3150211>
- [49] Dennis M. Ritchie. 1996. *The Development of the C Programming Language*. Association for Computing Machinery, New York, NY, USA, 671–698. DOI : <https://doi.org/10.1145/234286.1057834>
- [50] Fabian Schuiki, Florian Zaruba, Torsten Hoefler, and Luca Benini. 2021. Stream semantic registers: A lightweight RISC-V ISA extension achieving full compute utilization in single-issue cores. *IEEE Trans. Comput.* 70, 2 (Feb. 2021), 212–227. DOI : <https://doi.org/10.1109/TC.2020.2987314>
- [51] Matthew S. Simpson and Rajeev K. Barua. 2010. MemSafe: Ensuring the spatial and temporal memory safety of C at runtime. In *10th IEEE Working Conference on Source Code Analysis and Manipulation*. 199–208. DOI : <https://doi.org/10.1109/SCAM.2010.15>
- [52] Yulei Sui, Xiaokang Fan, Hao Zhou, and Jingling Xue. 2018. Loop-oriented pointer analysis for automatic SIMD vectorization. *ACM Trans. Embed. Comput. Syst.* 17, 2, Article 56 (Jan. 2018), 31 pages. DOI : <https://doi.org/10.1145/3168364>
- [53] TIOBE. 2022. TIOBE index. Retrieved from <https://www.tiobe.com/tiobe-index/>
- [54] Jie Zhou, John Criswell, and Michael Hicks. 2023. Fat pointers for temporal memory safety of C. *Proc. ACM Program. Lang.* 7, OOPSLA1, Article 86 (Apr. 2023), 32 pages. DOI : <https://doi.org/10.1145/3586038>
- [55] Zhen Li, Rohit Atre, Zia Ul-Huda, Ali Jannesari, and Felix Wolf. 2015. DiscoPoP: A profiling tool to identify parallelization opportunities. In *Tools for High Performance Computing 2014: Proceedings of the 8th International Workshop on Parallel Tools for High Performance Computing, October 2014, HLRS, Stuttgart, Germany*. Springer, 37–54.

Received 22 January 2024; revised 2 August 2024; accepted 21 August 2024