Distributing and Parallelizing Non-canonical Loops

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VMCAI 2023 16 January 2023

Loop Optimization

```
loop (0...n) {
    task_x
}
loop (0...n) {
    task_y
}
```

Fission or distribution

```
loop (0...n) {
    task_x
    task_y
}

⇔
```

Fusion or combination

```
loop (0...n/2) {
    task_x
    task_y
}
loop (n/2...n) {
    task_x
    task_y
}
```

 \Leftrightarrow

Splitting

...and many more strategies.

In This Work

We present a loop optimization algorithm based on **loop fission** transformation, to introduce **parallelization potential** in previously uncovered cases.

Potential for parallelism

- Identify independent operations
- Perform those operations in any order as system resources become available

Loop fission (or distribution)

- Break loop into multiple loops
- Each loop has the same iteration range
- Each takes part of original loop's body
- Some duplication may be needed

Conceptually: Distribute loops \Rightarrow parallelize \Rightarrow speedup in execution time

Our Technique

- Is applicable even when iteration space is unknown.
- Can be applied to any kind of loop: for, while, ...
- Can be applied to languages from high-level to intermediate representation.
- Is suitable for integration with automatic compilation and optimization tools.

Technique Overview

Start with a sequential imperative program.

- 1. Perform dependency analysis using data flow graphs (DFGs).
- 2. Build a dependency graph.
- 3. Compute condensation graph and compute its covering.
- 4. Create loop for each statement in covering.
- 5. Parallelize distributed loops.

Program Under Analysis

We consider simple deterministic imperative while language, with variables, expressions, commands, and parallel command. Program can include:

- Arrays and pure function calls,
- Arbitrarily complex update/termination conditions,
- Loop carried-dependencies, and
- Arbitrarily deep loop nests.

Certain memory accesses are out of scope: pointers, aliasing, etc.

Variables in Command C

We identify variables modified by (Out), used by (In), and occurring (Occ) in C.

$$E.g., C := t[e_1] = e_2,$$

$$\operatorname{Out}(\mathtt{C}) = \mathtt{t}$$

$$\operatorname{In}(\mathtt{C}) = \operatorname{Occ}(\mathtt{e}_1) \cup \operatorname{Occ}(\mathtt{e}_2)$$

$$\operatorname{Occ}(\mathtt{C}) = \mathtt{t} \cup \operatorname{Occ}(\mathtt{e}_1) \cup \operatorname{Occ}(\mathtt{e}_2)$$

We represent and analyze these dependencies using Data Flow Graphs (DFGs).

Data Flow Graph (DFG)

- A DFG is a matrix over a fixed semi-ring.
- Represents a weighted relation on set of variables involved in command C.
- 3 types of dependencies:

∞	dependence	$x \xrightarrow{dependence} x$
1	propagation	$\begin{array}{cccccccccccccccccccccccccccccccccccc$
0	reinitialization	z z

Constructing DFGs

For each command, we define a mapping from variables of command C to DFG. We write $\mathbb{M}(C)$ for the DFG of C.

Definition: Assignment

Given an assignment C, its DFG is given by:

$$\mathbb{M}(\mathtt{C})(\mathtt{y},\mathtt{x}) = \begin{cases} \infty & \text{if } \mathtt{x} \in \mathrm{Out}(\mathtt{C}) \text{ and } \mathtt{y} \in \mathrm{In}(\mathtt{C}) \text{ (Dependence)} \\ 1 & \text{if } \mathtt{x} = \mathtt{y} \text{ and } \mathtt{x} \notin \mathrm{Out}(\mathtt{C}) \text{ (Propagation)} \\ 0 & \text{otherwise} \text{ (Reinitialization)} \end{cases}$$

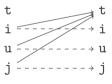
Representing DFGs

$$C := t[e_1] = e_2$$

$$\begin{split} \operatorname{Out}(\mathtt{C}) &= \{\mathtt{t}\} \\ \operatorname{In}(\mathtt{C}) &= \{\mathtt{i},\mathtt{u},\mathtt{j}\} \\ \operatorname{Occ}(\mathtt{C}) &= \{\mathtt{t},\mathtt{i},\mathtt{u},\mathtt{j}\} \end{split}$$

$\mathbb{M}(\mathtt{C})$

$\mathbb{M}(C)$ as a graph



Correction

All body variables of conditional and loop statements depend on its control expression. We apply loop correction to account for this dependency.

For e an expression and C a command, $Corr(e)_C$, is $E^t \times O$.

- E^t column vector with ∞ for variables in Occ(e) and 0 for other variables.
- O row vector with ∞ for variables in Out(C) and 0 for other variables.

Algorithm

- 1. Pick a loop at top level.
- 2. Construct a **dependence graph**, which uses the DFG.
- 3. Compute its **condensation graph** from dependence graph.
- 4. Compute a **covering** of the condensation graph.
- 5. Create a loop per element of the covering.

Dependence Graph

$$\begin{split} &\operatorname{In}(\mathtt{C}_1) = \{\mathtt{i},\mathtt{j}\} \\ &\operatorname{Out}(\mathtt{C}_3) = \{\mathtt{i}\} \end{split}$$



Definition: Dependence graph

The dependence graph of the loop $W := \text{while e do } \{C_1; \dots; C_n\}$ is the graph whose vertices is the set of commands $\{C_1; \dots; C_n\}$, and there exists a directed edge from C_i to C_j if and only if there exists variables $x \in Out(C_i)$ and $y \in In(C_i)$ such that $M(W)(y,x) = \infty$.

Condensation Graph & Covering

Given a dependence graph, its condensation graph $G_{\!W}$ is the graph whose

- vertices are strongly connected components (SCCs) and
- edges are the edges whose source and target belong to distinct SCCs.

We then find the proper saturated covering of G_W . For graph G,

- covering is a collection of subgraphs such that $G = \cup_{i=1}^{j} G_i$.
- saturated covering is a covering such that for all edges with source in G_i , its target belongs to G_i as well.
- It is *proper* if none of the subgraph is a subgraph of another.

Constructing Output

Lastly, we construct loop $\tilde{\mathbb{W}}$ by insert a loop for each element in the proper saturated covering.

If \tilde{W} contains multiple loops, parallelize \tilde{W} .

Identify In and Out variables

```
\begin{split} \operatorname{Out}(\mathtt{C}_1) &= \{\mathtt{x}\} \\ \operatorname{In}(\mathtt{C}_1) &= \{\mathtt{A},\mathtt{i},\mathtt{j},\mathtt{r}\} \\ & \vdots \\ \operatorname{Out}(\mathtt{C}_3) &= \{\mathtt{s}\} \\ \operatorname{In}(\mathtt{C}_3) &= \{\mathtt{s},\mathtt{j},\mathtt{x}\} \\ & \vdots \\ \operatorname{Out}(\mathtt{C}_5) &= \{\mathtt{j}\} \\ \operatorname{In}(\mathtt{C}_5) &= \{\mathtt{j}\} \end{split}
```

Construct DFGs for each command

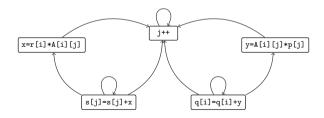
Compose DFGs of commands $\mathbb{M}(C_1;\ldots;C_n)$ and apply loop correction $E^t \times O$

$$\mathbb{M}(C) = \begin{bmatrix} i & j & m & x & y & A & r & s & p & q \\ i & 1 & \cdot & \cdot & \infty & \infty & \cdot & \cdot & \cdot & \cdot & \infty \\ j & \cdot & \infty & \cdot & \infty & \infty & \cdot & \cdot & \infty & \cdot & \infty \\ k & \cdot & \infty & 1 & \infty & \infty & \cdot & \cdot & \infty & \cdot & \infty \\ k & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \infty & \cdot & \cdot \\ k & \cdot & \cdot & \infty & \infty & 1 & \cdot & \cdot & \cdot & \infty \\ k & \cdot & \cdot & \infty & \infty & 1 & \cdot & \cdot & \cdot & \cdot \\ k & \cdot & \cdot & \infty & \infty & 1 & \cdot & \cdot & \cdot & \cdot \\ k & \cdot & \cdot & \infty & \infty & \cdot & \cdot & 1 & \cdot & \cdot & \cdot \\ k & \cdot & \cdot & 0 & \infty & 0 & \cdot & \cdot & 1 & \cdot & \cdot \\ k & \cdot & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ k & \cdot & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

 $[\]mathbb{M}(C) = \mathbb{M}(C_5) \times \cdots \times \mathbb{M}(C_1) + \operatorname{Corr}(e)_C$

Step 4 of 6

Construct a dependence graph. Vertices are the set of commands $\{C_1; \dots; C_n\}$. Add directed edge from C_i to C_j iff $\exists x, y$, where $x \in \mathrm{Out}(C_j)$ and $y \in \mathrm{In}(C_i)$ and $\mathbb{M}(\mathbb{W})(y,x) = \infty$.



Construct a condensation graph and proper saturated covering.



Distribute loops and parallelize.

$$\tilde{\mathbb{W}} := \text{ parallel} \left\{ \begin{array}{l} \text{while } (j < m) \ \{ \\ x = r[i] * A[i][j]; \\ s[j] = s[j] + x; \\ j + +; \\ \} \end{array} \right\} \quad \left\{ \begin{array}{l} \text{while } (j < m) \ \{ \\ y = A[i][j] * p[j]; \\ q[i] = q[i] + y; \\ j + +; \\ \} \end{array} \right\}$$

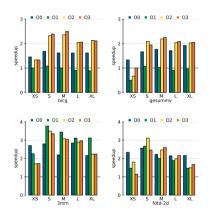
Experimental Evaluation



- Our artifact¹ is a collection of benchmarks.
- Mapped imperative syntax to C language.
- Used OpenMP directives to parallelize.
- Measured on standard benchmark suites, partially converted to while loops.
- Compared to an alternative loop transformation tool.

¹Clément Aubert et al. Distributing and Parallelizing Non-canonical Loops — Artifact. Version 1.0. Sept. 2022. DOI: 10.5281/zenodo.7080145. URL: https://github.com/statycc/loop-fission.

Experimental Results



- Enables transformation and parallelization of loops ignored by alternative methods.
- Non-canonical loops: speedup upper-bounded by the number of parallelizable loops produced by transformation.
- Canonical loops: comparable to alternative methods in speedup potential.
- Demonstrated automatic insertion of parallel directives and practicality of this technique.

Conclusion

- Introduced an automatable loop optimization technique that adds parallelization potential to imperative programs.
- It is loop and language-agnostic many possible applications.
- We presented the algorithm to perform the loop optimization.
- Experimental results demonstrate expected performance gain see artifact
- See our paper for proof of preservation of semantic correctness.