Static Versioning in the Polyhedral Model

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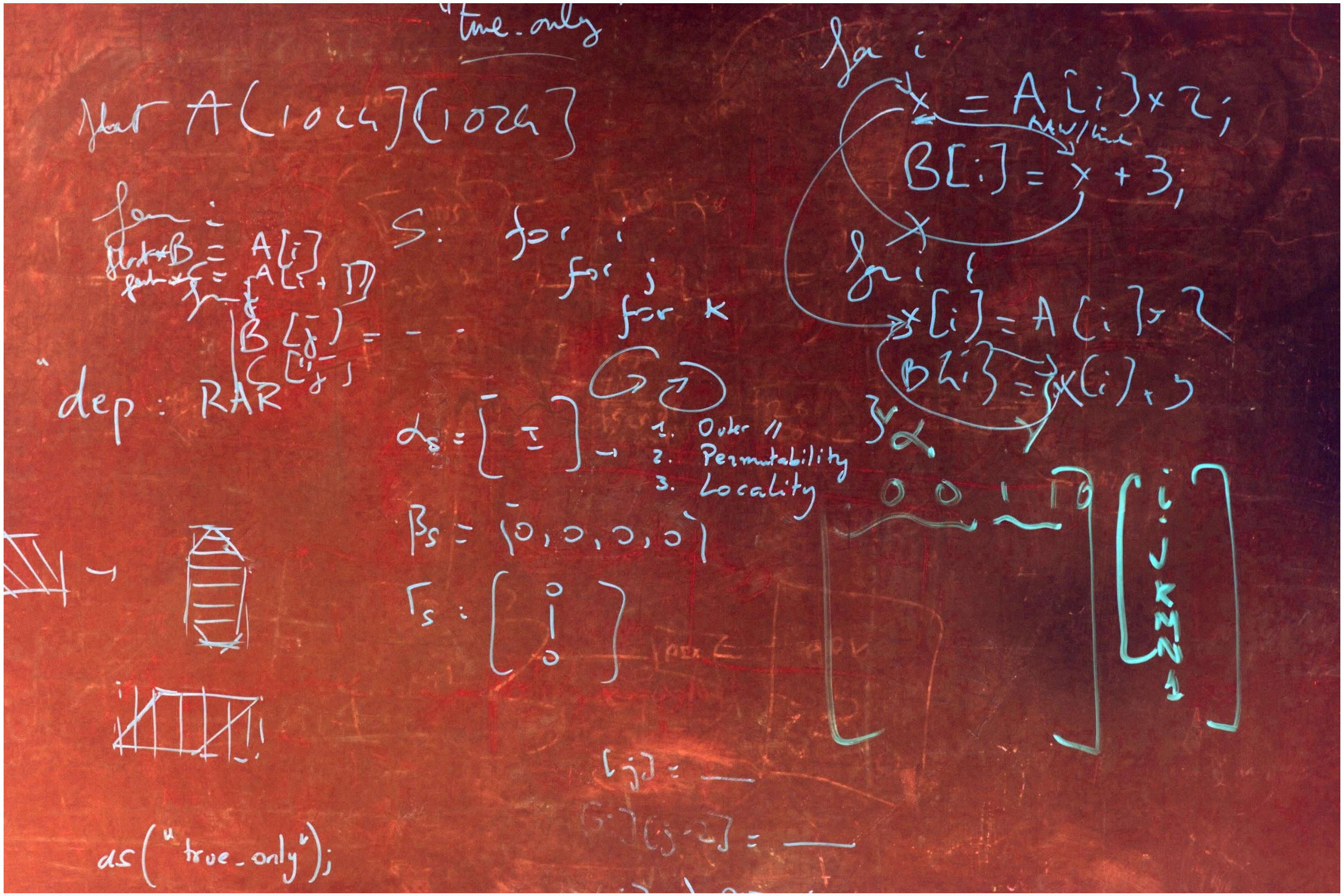


Outline

- Who we are: Reservoir Labs
- Polyhedral versioning: background & motivation
- Approach
- Results

Reservoir Labs

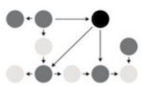
Technology Expertise

High Performance Computing

R-Stream
Automatic Parallelization and Mapping Through Polyhedral Model

LLVM
Customization for Advanced Supercomputers

Networking



GradientGraph
Network Optimization

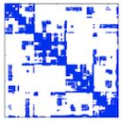
R-Core
Packet Path Accelerator

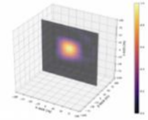
Cybersecurity

R-Scope
Network Sensor Visibility Enterprise Security

ENSIGN: Cyber
Spectral Hypergraph Analytics

Algorithms





Asymptotic Improvements to Physical Simulation, Optimization, and Inverse Problems

https://www.reservoir.com/
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Polyhedral Versioning
Background & Motivation

Versioning (a.k.a Multi-Versioning)

What is it?

- Observation: **different optimization opportunities** arise under **different run-time conditions**

- With versioning, compiler generates:
  - Multiple versions of a code region
  - Code to select the most appropriate version at run-time

Traditional example

- Suppose alias analysis cannot statically disambiguate two pointers

```
int * p1, *p2;
...
if (mayAlias(p1, p2)) {
   // code optimized assuming aliasing
else {
   // code optimized assuming non-aliasing
}
```

- If these pointers were not aliased, more instructions could be run in parallel [Sampaio17]

Motivation

Deep Learning (DL) Optimization

- DL networks can re-use layers with varied input tensor sizes
  - Explored this via our R-Stream TensorFlow [TF] front-end TFRCC [TFRCC]

- R-Stream maps differently for different fixed input sizes
  - Mapping refers to polyhedral compiler's optimization phase

- More and more DL networks have variable-size inputs
  - Assume: sizes are parameters to the optimized function
  - We may not know anything about them
  - A single mapping cannot be optimal for all sizes
  - Need to be more adaptive to sizes

Polyhedral versioning

Our solution

Run-time defined parameters (e.g., tensor sizes)

Code (e.g., outlined NN code)

Constraints for parametric affine domain over a1,...,an

Call to a version of func

This function...

```
func (...a1,...,an,...) {
        ...
        ...
}
```

...is compiled to this

```
versioned_func(...,a1,...,an,...) {
     if (PD1) {
          if (PD2) {
               func_1(a1,...,an);
          } else {
               func_2(a1,...,an);
          }
     } else {
          if (PD3) {
               func_3(a1,...,an);
          } else {
               ...
          }
     }
}
```

Other approaches

- Pre-compilation: User incorporates knowledge of run-time parameter values into program logic (R-Stream allows this via #pragma)

```
#pragma rstream map "context:N>=128,N<=1024"
void matmult(real_t A[N][N], real_t B[N][N], real_t C[N][N]) {
  int i, j, k;
  for (i = 0; i < N; i++) {
    for (j = 0; j < N; j++) {
      C[i][j] = 0.0;
      for (k = 0; k < N; k++) {
        C[i][j] += A[i][k] * B[k][j];
      }
    }
  }
}
```

- Just-In-Time: use polyhedral model in non-polyhedral codes
  - PolyJIT: find run-time polyhedral cases, point-wise versioning
  - Apollo: calls Pluto at runtime to optimize code
    - Recent run-time versioning + mini-auto-tuning support

Polyhedral Intermediate Representation (IR)

Correspondences

Polyhedral terms	Functional terms
1. Generalized dependence graph (GDG) ○ GDG parameters	1. Program function ○ Formal parameters
2. GDG hierarchy ○ Parent / child GDGs	2. Function call graph ○ Caller / callee
3. Specialized (aka versioned) GDG	3. Versioned function
4. Context of a GDG ○ Affine constraints over GDG parameters ○ Used in optimization decisions	4. Function domain / preconditions

Approach

Approach outline

Main steps:

1. (Auto) generate useful GDG parameter domains for versions
   - Illustration: processor placement

2. Incorporate and encode versioning decisions into the mapping process

3. Generate versioned code

Determine GDG version domains

Processor Placement (1/2)

- Placement pass: associate placement function to each polyhedral statement
  Pl: $\mathbb{Z}^{\text{param}} \times \mathbb{Z}^{\text{iterations}} \rightarrow \mathbb{Z}^{\text{grid\_dims}}$

- Occupation test
  - loop trip count >= c x processor grid size
  - c : "occupancy", factor we want to occupy (½ of the grid, 3x the grid size, ...)
  - If true: place along the loop
  - Otherwise, try another loop

- When trip count involves unbounded GDG parameters, mapper assumes they are large enough
  - Unchecked assumption

Determining GDG version domains

Processor Placement (2/2)

- t(N) : parametric loop trip count
- pg(k) : grid size along targeted dim k
- When t(N) cannot be bounded by a constant
  - Schedule the mapping of a GDG version
  - "Tell the mapper" to consider the following affine range (i.e., not large enough assumption)

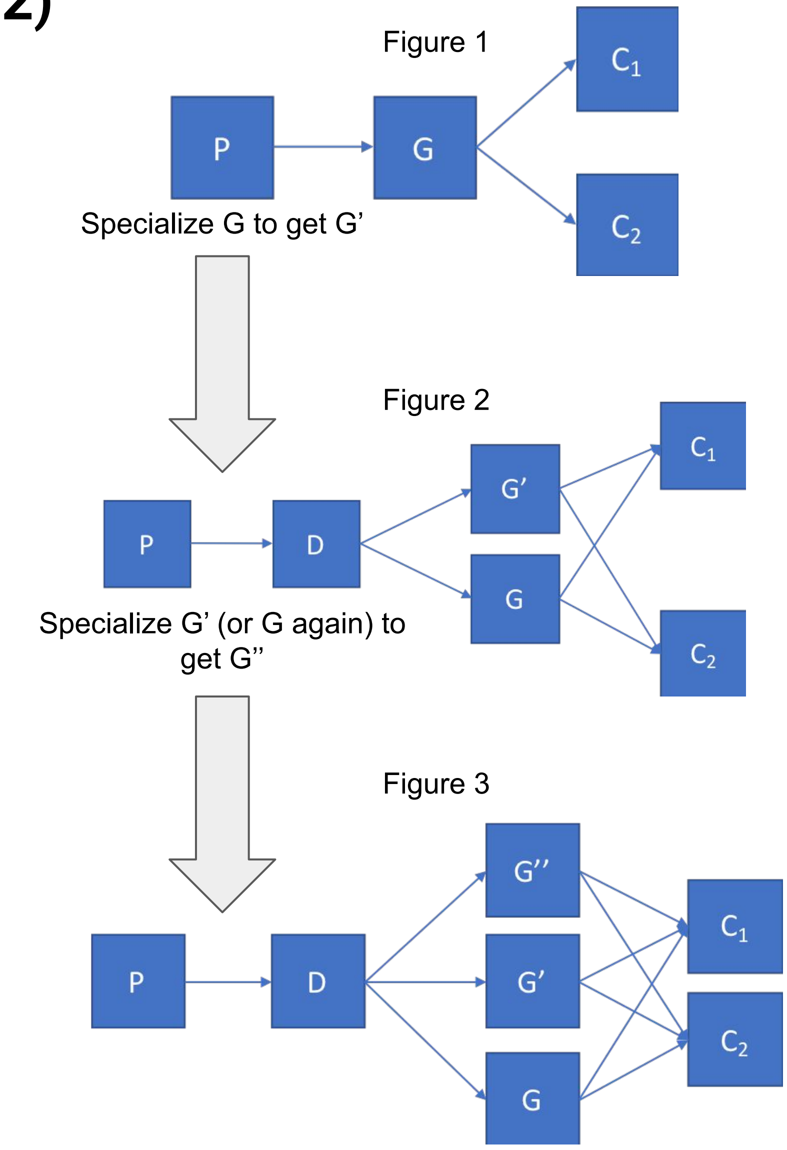
$$t(N) \leqslant c * pg(k)$$

Mapping and encoding versions (1/2)

- Introduce polyhedral statement called a "SpecializeOp"
  - Maintains versions of a GDG ("specialized GDGs")
- Introduce a specializer GDG to hold a SpecializeOp
  - At codegen: conditionally calls the versioned functions
- A specialized GDG comes from "specializing a GDG", that is
  - Clone the GDG
  - Intersect cloned GDG's context with given domain
  - Here, given domain will be $t(N) \leqslant c * pg(k)$

Mapping and encoding versions (2/2)

- Insert specialized GDG into existing GDG hierarchy
  - D : "specializer GDG"
  - P : "parent GDG" of G
  - C_1 and C_2 : the "child GDGs" of G
- After insertion, the specialized GDG is scheduled for mapping
  - Start where mapping was at for the input GDG (e.g., right at placement pass)



Code Generation (1/2)

- Generate nested if/else for the specializer GDG that
  - avoids explicit polyhedral differences (ugly code, complexity)
  - executes only one version for any parameter value

- Note: extra degree of liberty when specialized domains overlap
  - Unexploited here

- Naive approach
  - C_i = specialized GDG G_i's context
  - $\#(C_i)$ = # of constraints in C_i
  - N = total # of contexts
  - Redundantly check constraints
  - Nested constraints depth for G_i : $\sum_{j=1}^{i} \#(C_j)$

```
if (C1) {
     call the function lowered for G1
} else if (C2) {
     call the function lowered for G2
}
     .
     .
     .
else if (Cn) {
     call the function lowered for Gn
}
```

Code Generation (2/2)

- Outermost conditions: pick a constraint that divides the contexts non-trivially into included/not included GDG contexts
- Following properties:
  - No constraint checked more than once for any parameter values
  - Total number of constraints to get to G_i is $\leqslant N + \#(C_i)$
  - See paper for proof
- Dividing as evenly as possible helps drive N to $\log_2(N)$ in upper bound

Evaluation

Evaluation

Specifications

- Test machine processor info:
  - 1 socket, 8 cores/socket and 2 threads/core
  - Processing grid size: [16]

- Three test programs
  - **fc**: a fully connected layer where input/output sizes are equal
  - **convolution_googlenet**: 1st convolution of GoogLeNet
  - **maxpool_resnet**: a residual NN layer that uses MaxPooling

- Test programs are functions that have one run-time defined parameter
  - Here, versioned code is branched on this parameter's value
  - For small parameter values, versioned program executes further optimized code
  - For large parameter values, versioned and non-versioned programs execute virtually the same code

Evaluation

R-Stream mapping, OpenMP target

For each (layer, occupancy setting, param value):

1. Compile program w/ versioning and w/o versioning

2. Run versioned program with fixed param value for 5 trials
   a. Dampens OpenMP variability

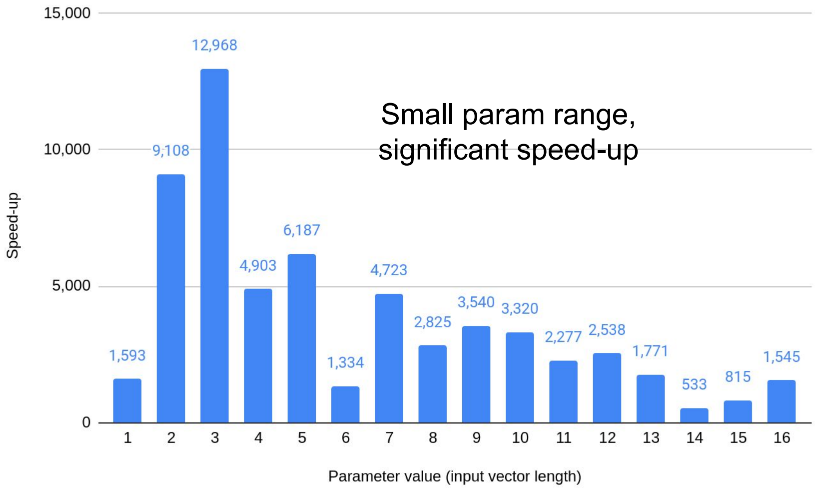
3. Run the non-versioned with the fixed param value for 5 trials

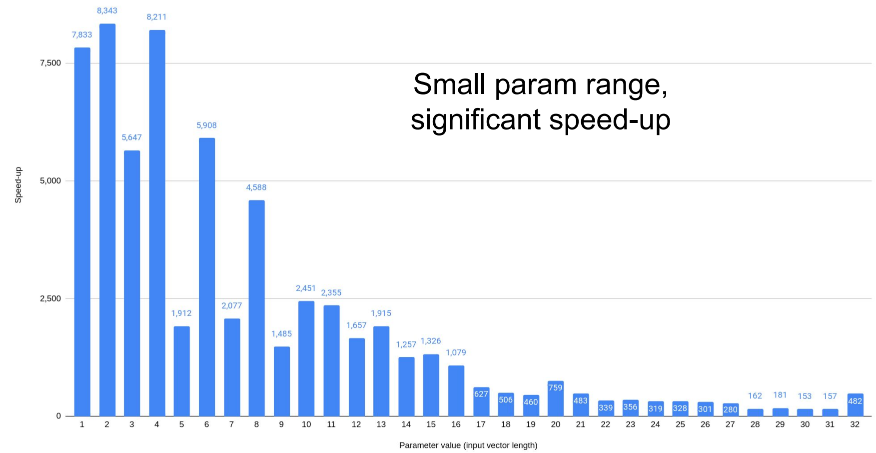
4. Compute run time speed-up

- Occupancy values:
  - 100% (full) and 200% (double)
  - 200% is to leverage dynamic load-balancing of OpenMP

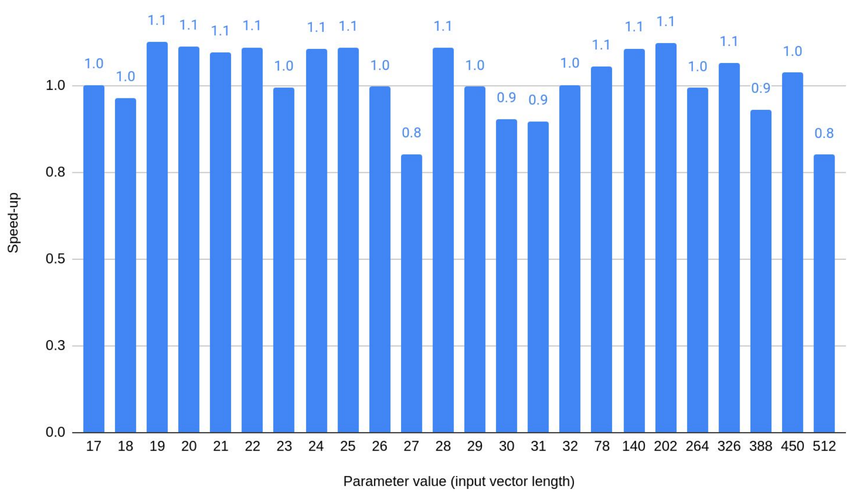
Results

Versioning speedup



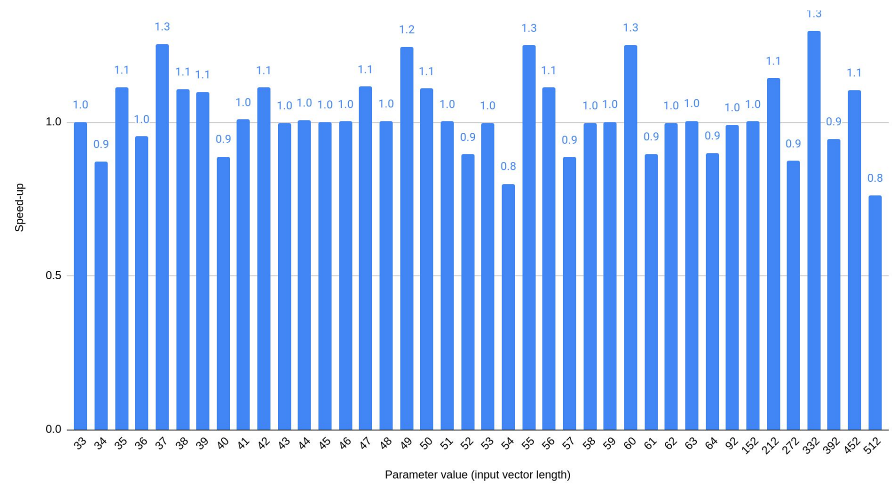


Large param range, same performance



fc, c=1

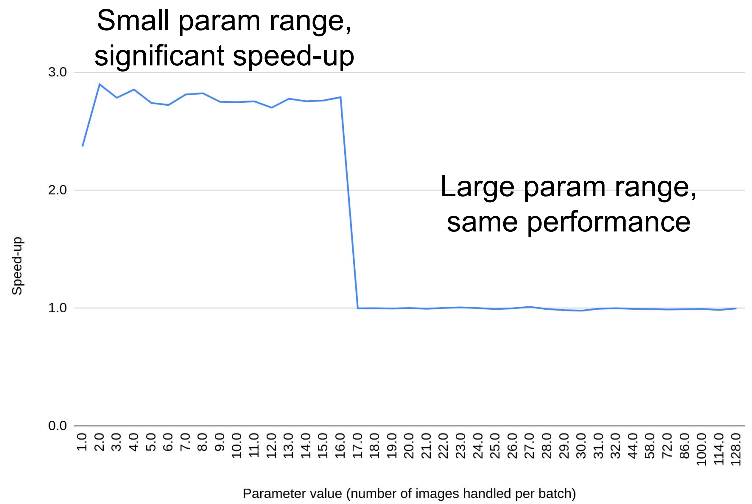
Large param range, same performance

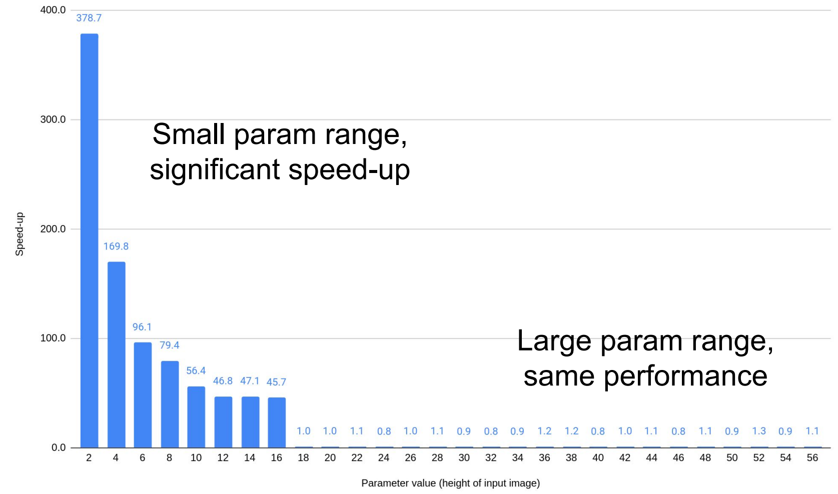


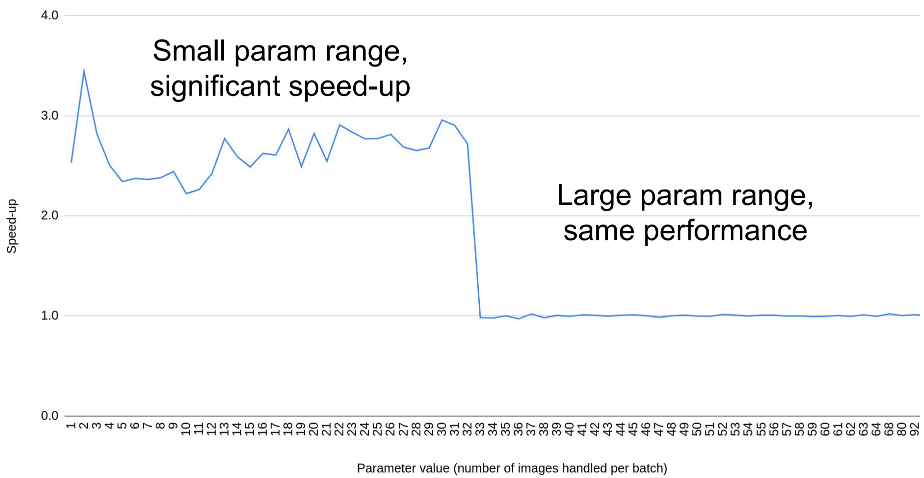
fc, c=2

Results

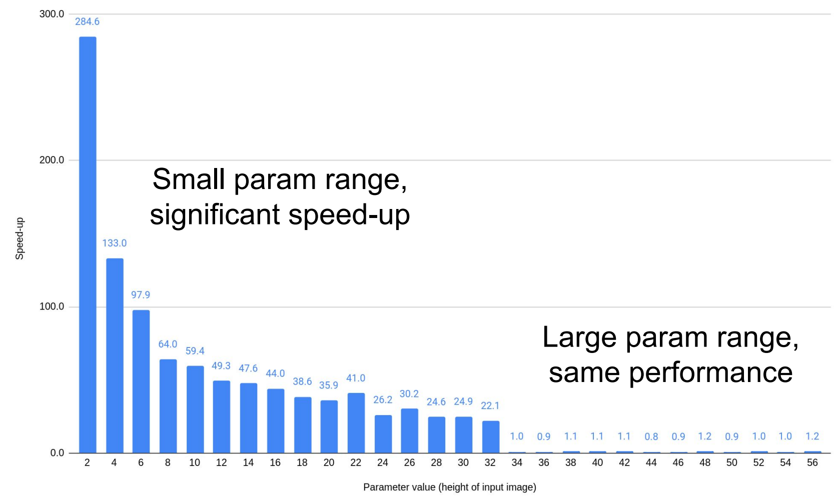
Versioning speedup







convolution_googlenet



maxpool_resnet

Results

Versioned GDG vs non-versioned

- Speedup was due to sequential version being faster than parallel version for small size parameters (expected)

- Example layers resulted in sequential vs. parallel
  - Want to find examples where different placement choices are made

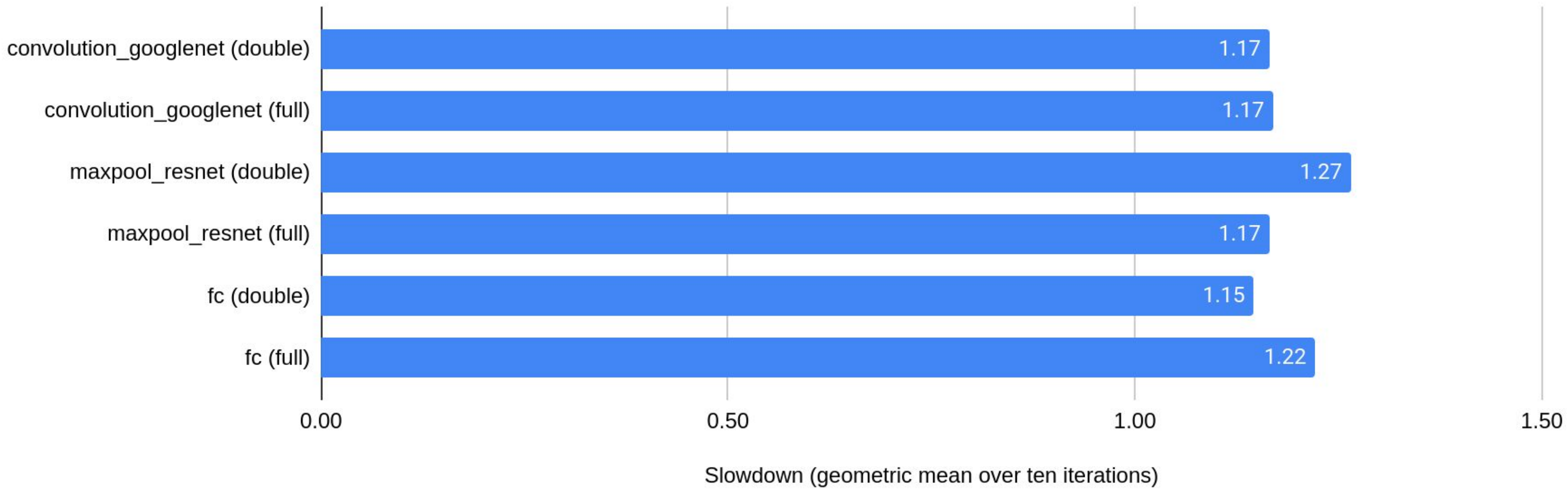
- “Bump” between versions
  - Versioning domain inequality can be improved
  - Occupation test is very simple but not optimal

- Simple target (OpenMP) and pass (processor placement)
  - Useful to understand basic problematic
  - More tradeoffs and questions w/ other passes & targets

Results

Compilation time

Upshot: low overhead



Tradeoff between partial mapping (placement & onward) vs. full mapping

- Full: More optimization opportunities, but higher compilation time

Thank You

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