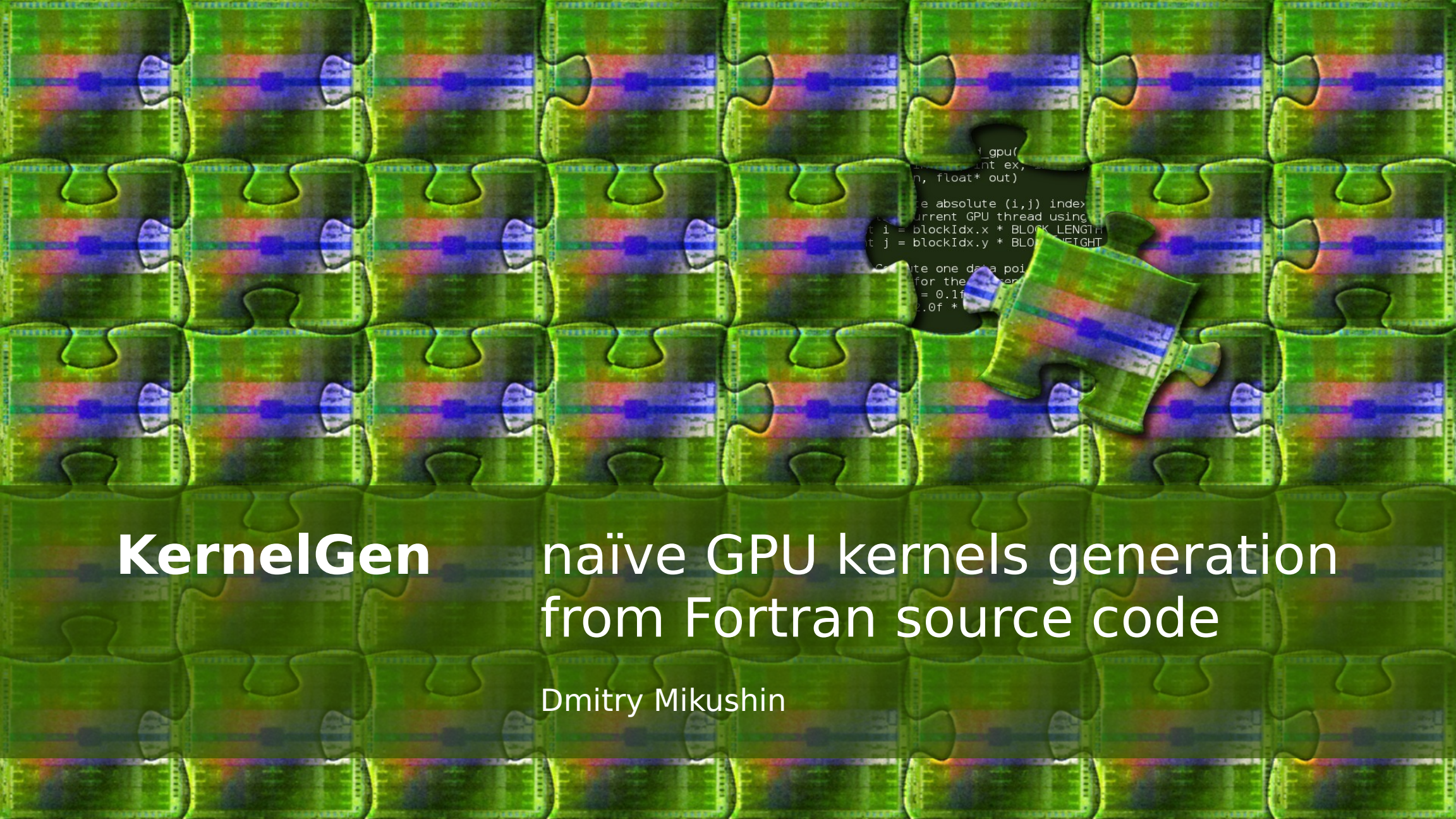


KernelGen

naïve GPU kernels generation from Fortran source code

Dmitry Mikushin

Contents

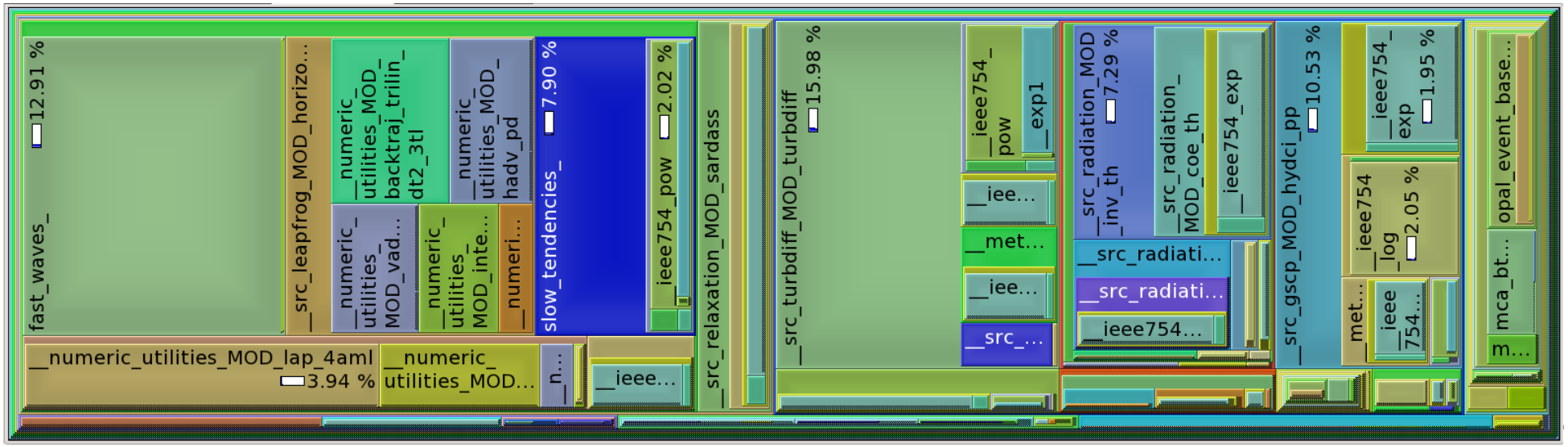
- Motivation, target, analysis
- Assembling our own toolchain
- Toolchain usecase: axpy example
- Development schedule

1. Motivation, target, analysis

Why generation?

The need of huge numerical models porting onto GPUs:

- All individual model blocks have too small self perf impact (~10%), resulting into small speedups, if only one block is ported



Why generation?

The need of huge numerical models porting onto GPUs:

- A lot of code requiring lots of similar transformations
- A lot of code versions with minor differences, each requiring manual testing & support
- COSMO, Meteo-France: science teams are not ready to work with new paradigms (moreover, tied with propriety products), compute teams have no resources to support a lot of new code

Why generation?

So, in fact science groups are ready to start GPU-based modeling, if three main requirements are met:

- Model works on GPUs without specific extensions
- Model works on GPUs and gives accurate enough results in comparison with control host version
- Model works on GPUs faster

Our target

Port already parallel models in Fortran onto GPUs:

- Conserving original Fortran source code (i.e. keeping all C/CUDA/OpenCL in intermediate files)
- Minimizing manual work on specific code (i.e. developed toolchain is expected to be reusable with other codes)

“Already parallel” means the model gives us some data decomposition grid to map 1 GPU onto 1 MPI process or thread.

Similar tools: PGI CUDA Fortran

Not really similar:

- Same manual coding as with CUDA C we want to minimize
- PGI's own Fortran language extensions

Similar tools: PGI Accelerator

Very similar, but:

- Still needs to set manual annotations on loops
- Is a propriety “black box” with limited info about implemented features

Similar tools: PathScale HMPP

Almost same as PGI Accelerator:

- Also has CAPS for automatic capable loops lookup
- Introduces some inapplicable constraints on accelerated loops, for instance, being a pure function (not really a problem with partial link-time kernels compilation)
- Tries to standardize OpenHMPP
- HMPP is a “black box”, but PathScale host compiler recently became open-source

Similar tools: f2c-acc

Actually, a work-in-progress equivalent for PGI Accelerator

- Still a lot of manual assistance needed

Conclusion

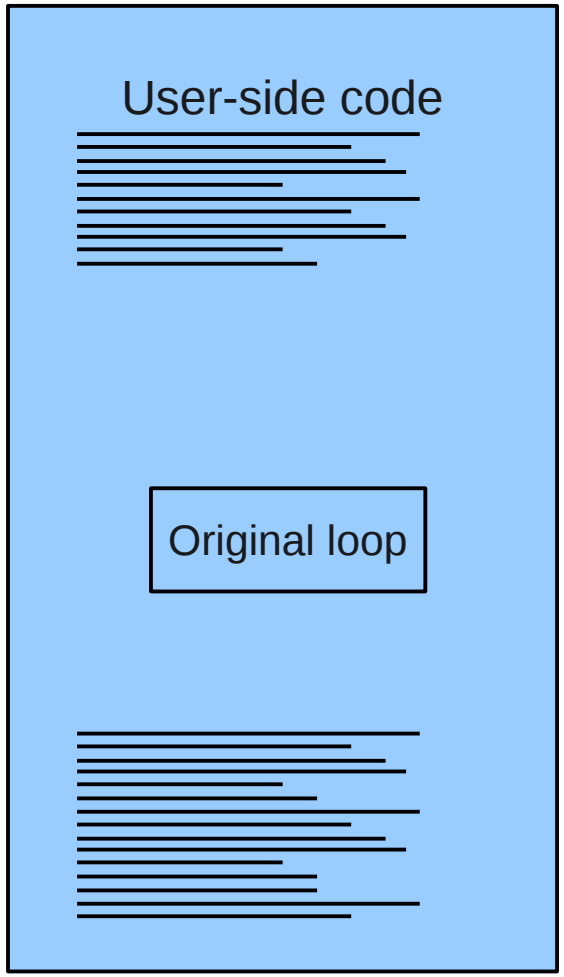
- Clearly, it would be a right decision to use f2c-acc or PGI or HMPP, if they could support GPU kernels generation without directives/annotations
- While they don't, adopting models is a complicated long-term task
- Can we build our own toolchain with dependencies analysis instead of directives?

2. Assembling our own toolchain

Ingredients

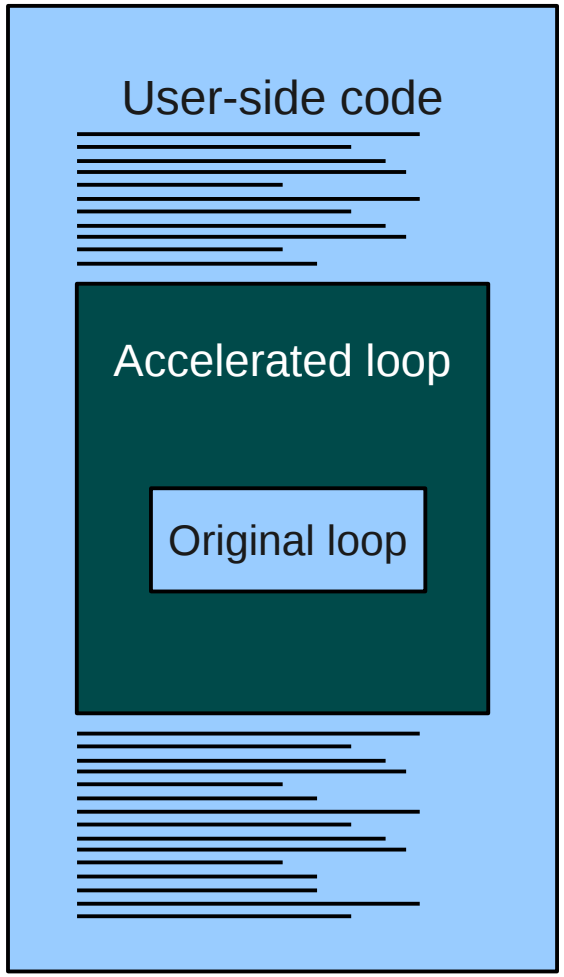
- **Compiler** – split original code into host and device parts and compile them into single object
  - Code splitter (source-to-source preprocessor)
  - Target device code generator
- **Runtime library** – implementation of specific internal functions used in generated code
  - Data management
  - Kernel invocation
  - Kernel results verification

Runtime workflow



We start with original source code, selecting loops suitable for device acceleration.

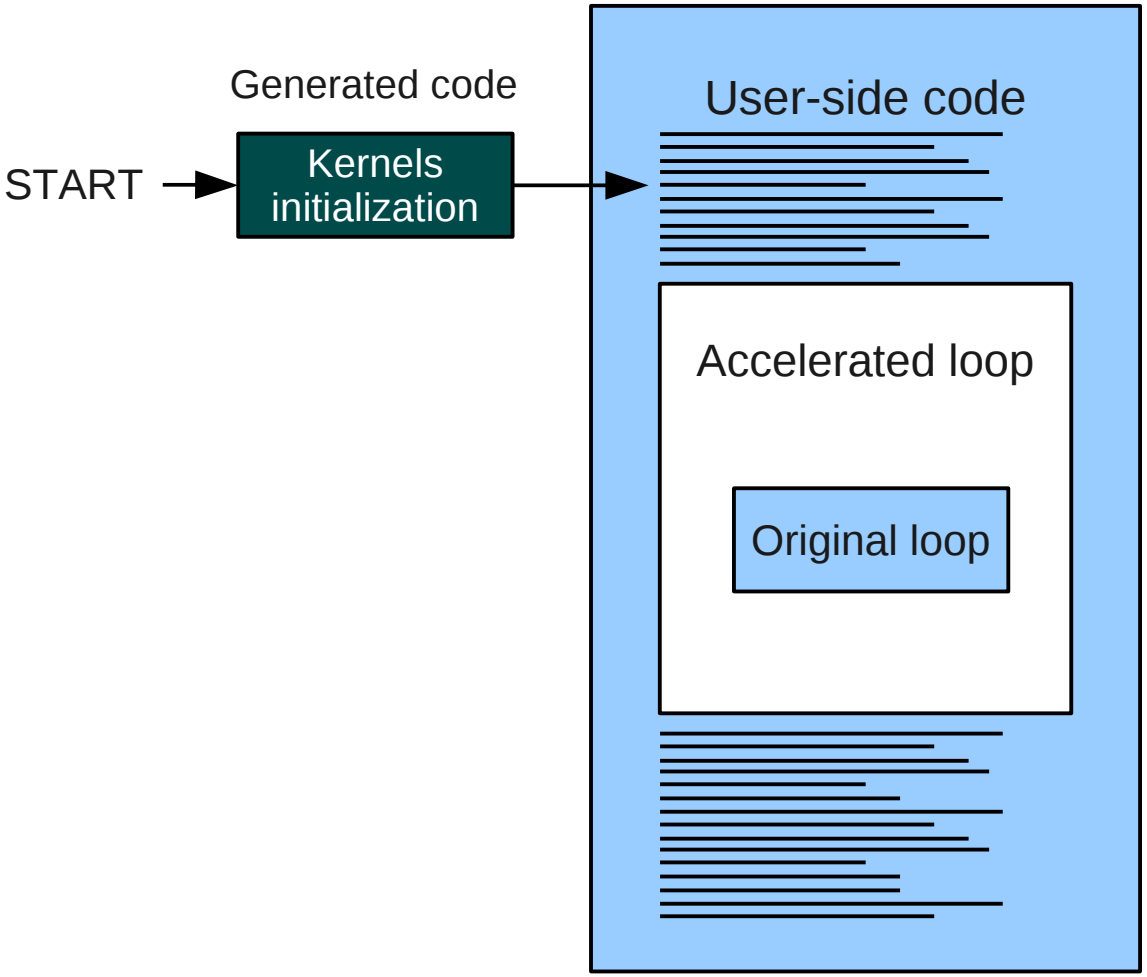
Runtime workflow



Equivalent device code is generated for suitable loops.

(see “Code generation workflow” for details)

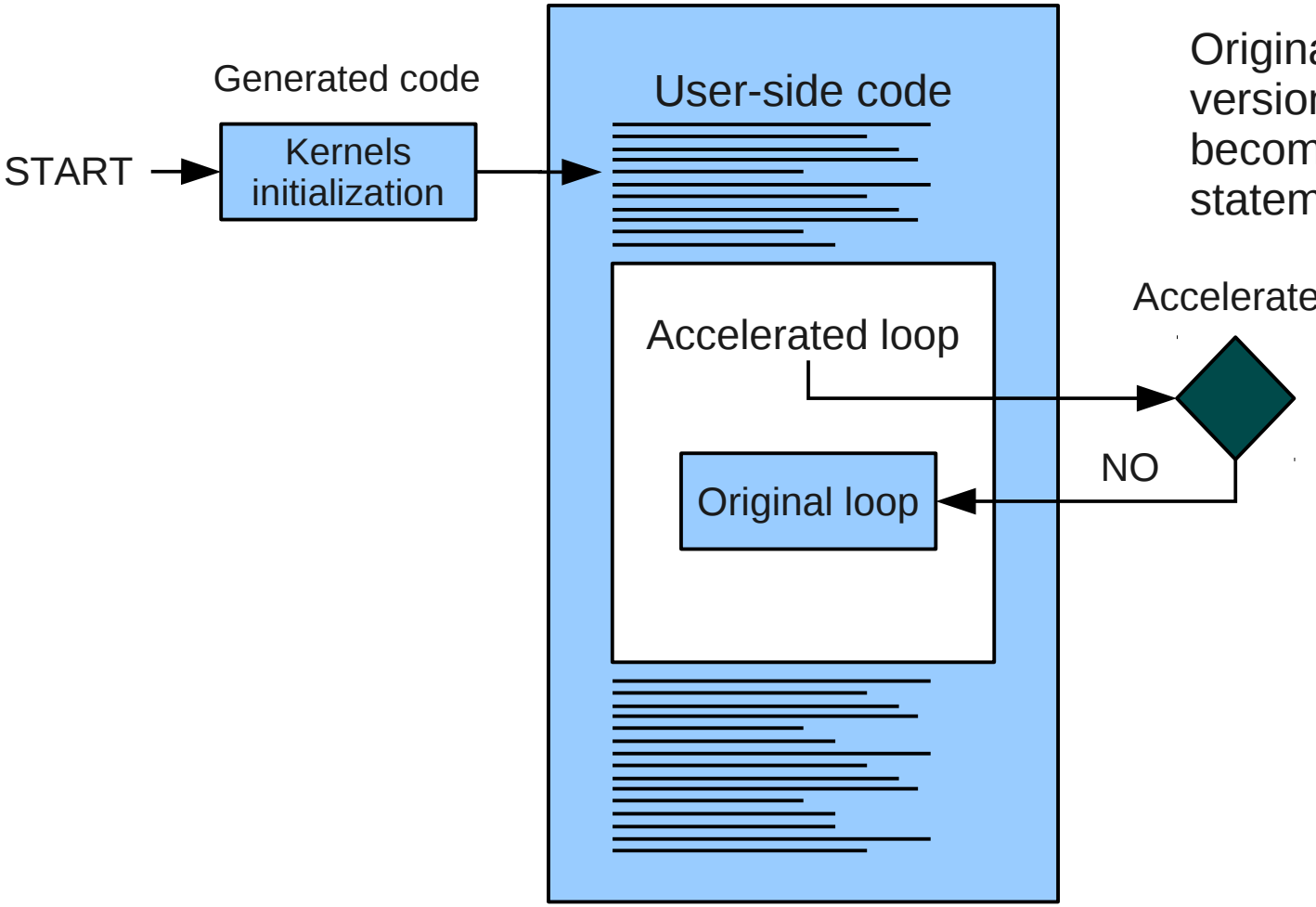
Runtime workflow



Equivalent device code is generated for suitable loops.

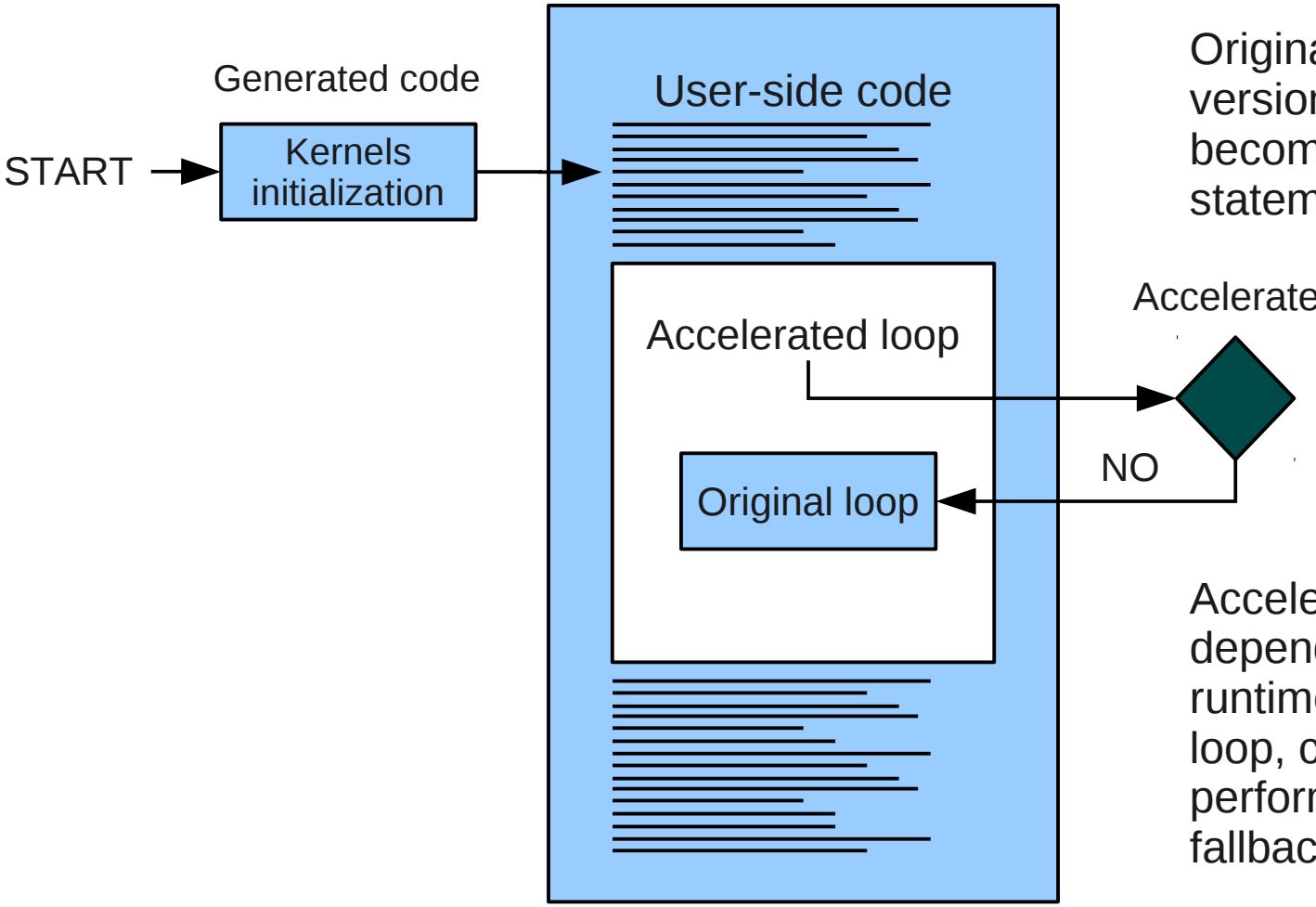
Additionally global constructors are generated to initialize configuration structures (with status, profiling, permanent dependencies, etc.) for each kernel.

Runtime workflow



Original and accelerated versions of the same loop become two branches of if-statement.

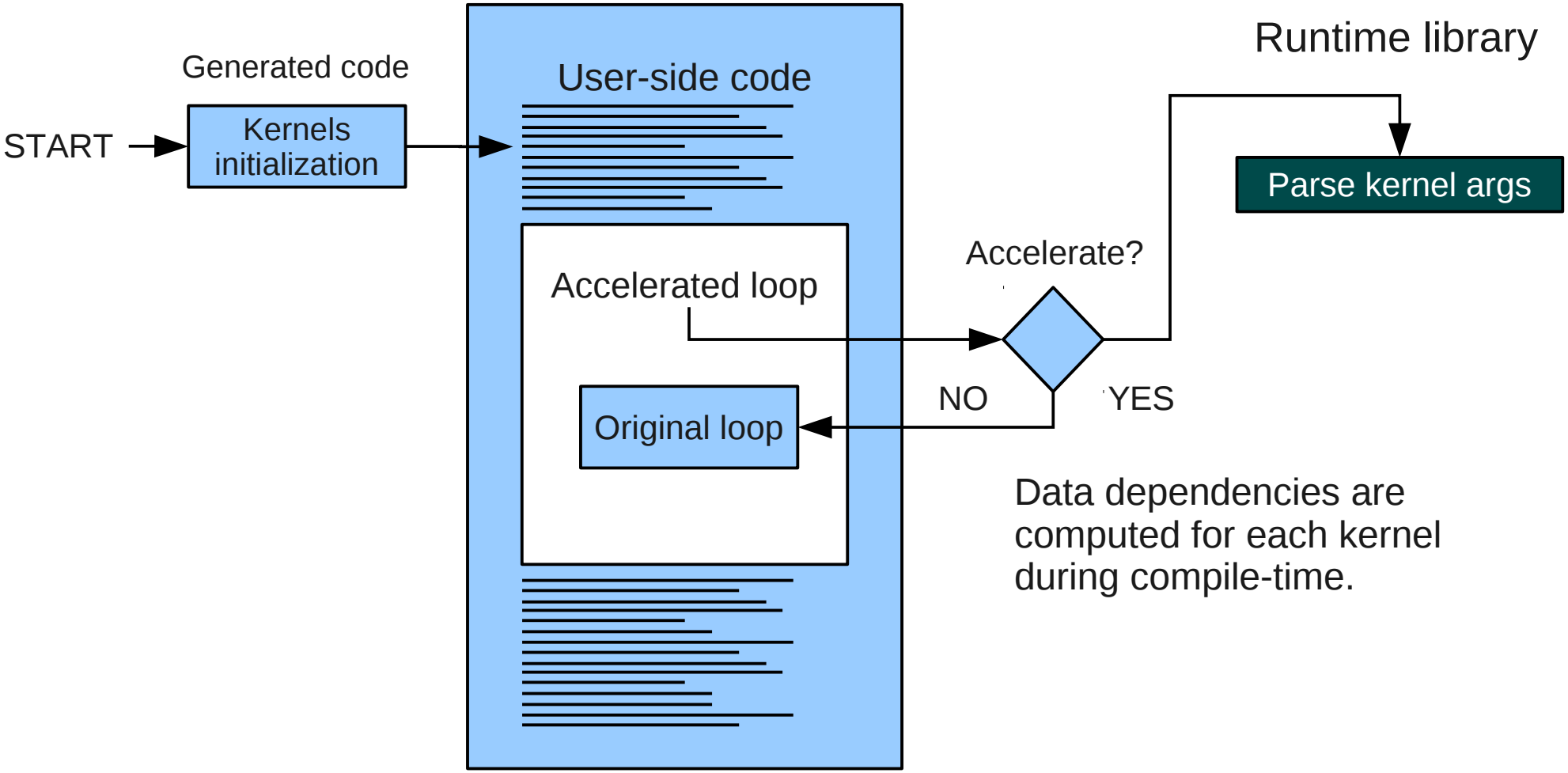
Runtime workflow



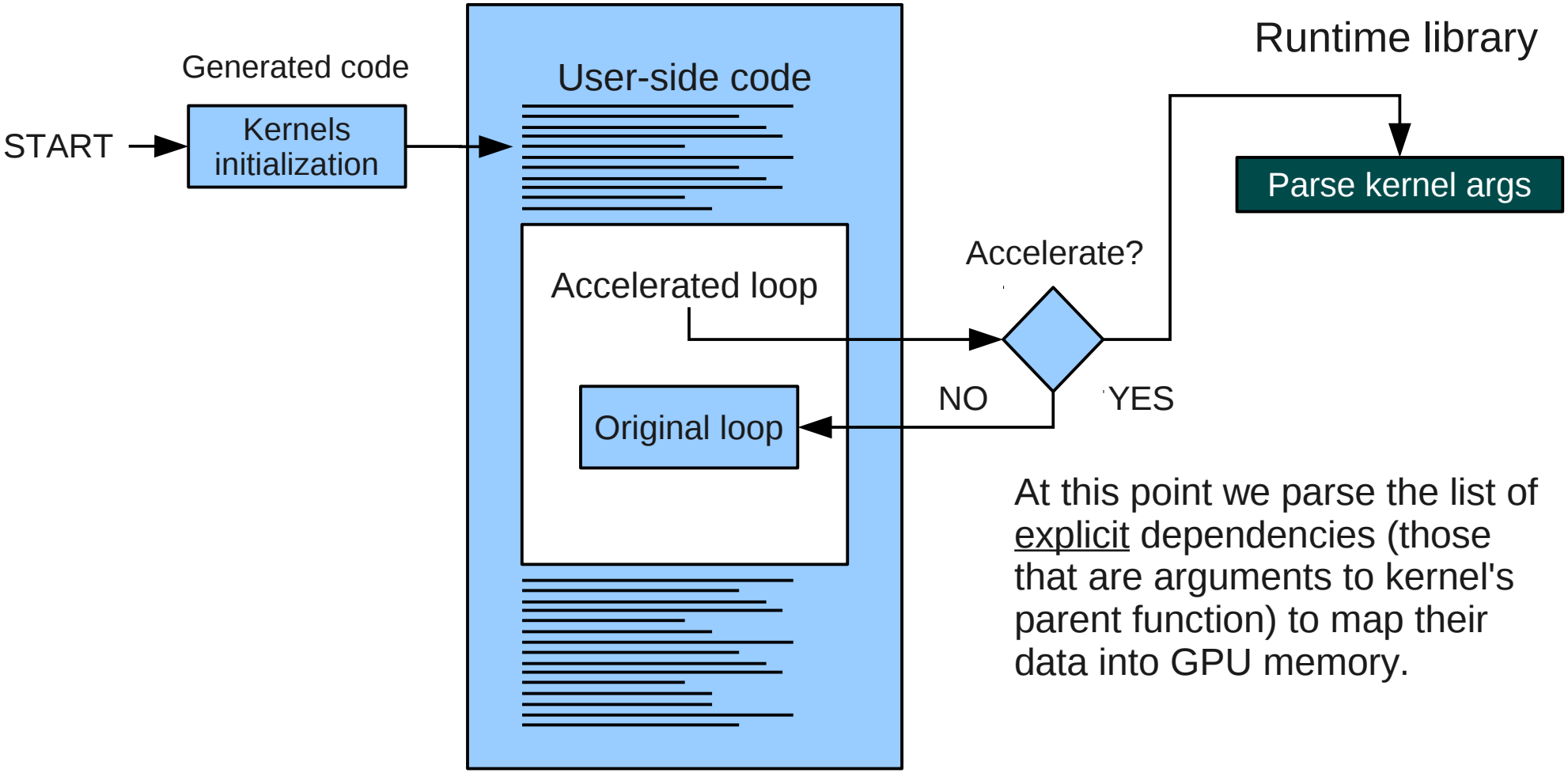
Original and accelerated versions of the same loop become two branches of if-statement.

Accelerated loop is selected, depending on the number of runtime properties (not failing loop, correct results, better performance, etc.); otherwise – fallback to original version.

Runtime workflow

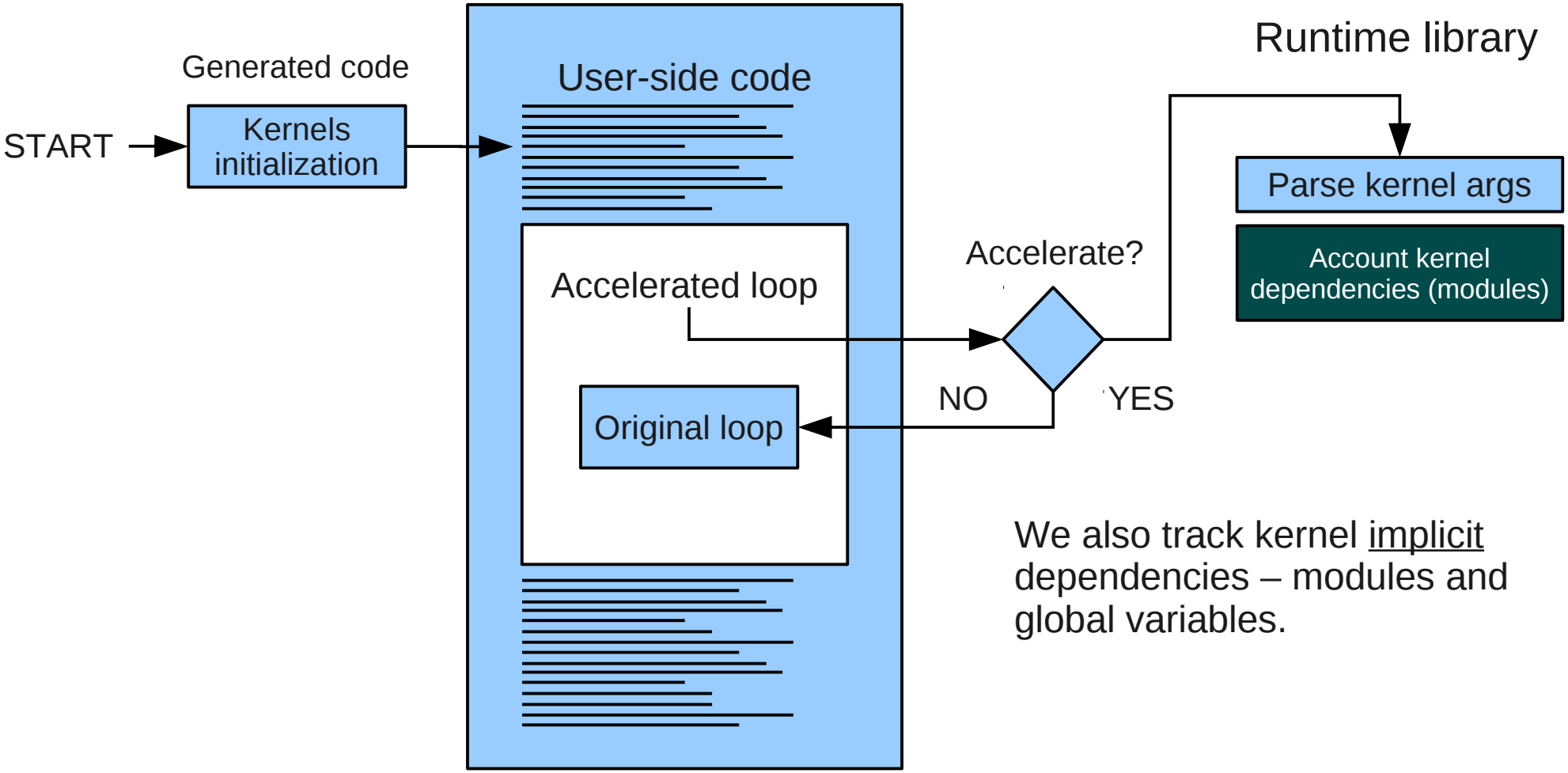


Runtime workflow



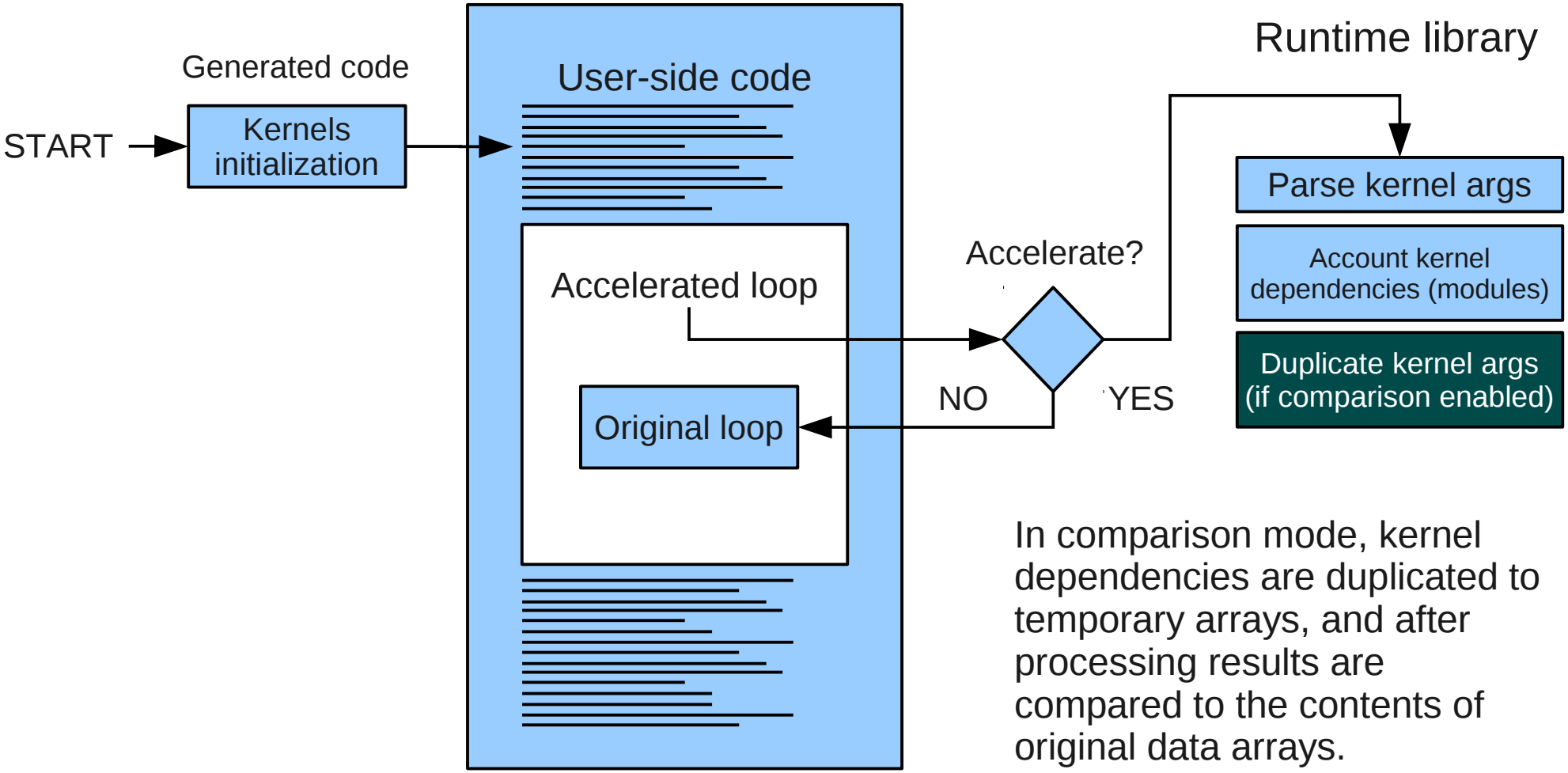
At this point we parse the list of explicit dependencies (those that are arguments to kernel's parent function) to map their data into GPU memory.

Runtime workflow



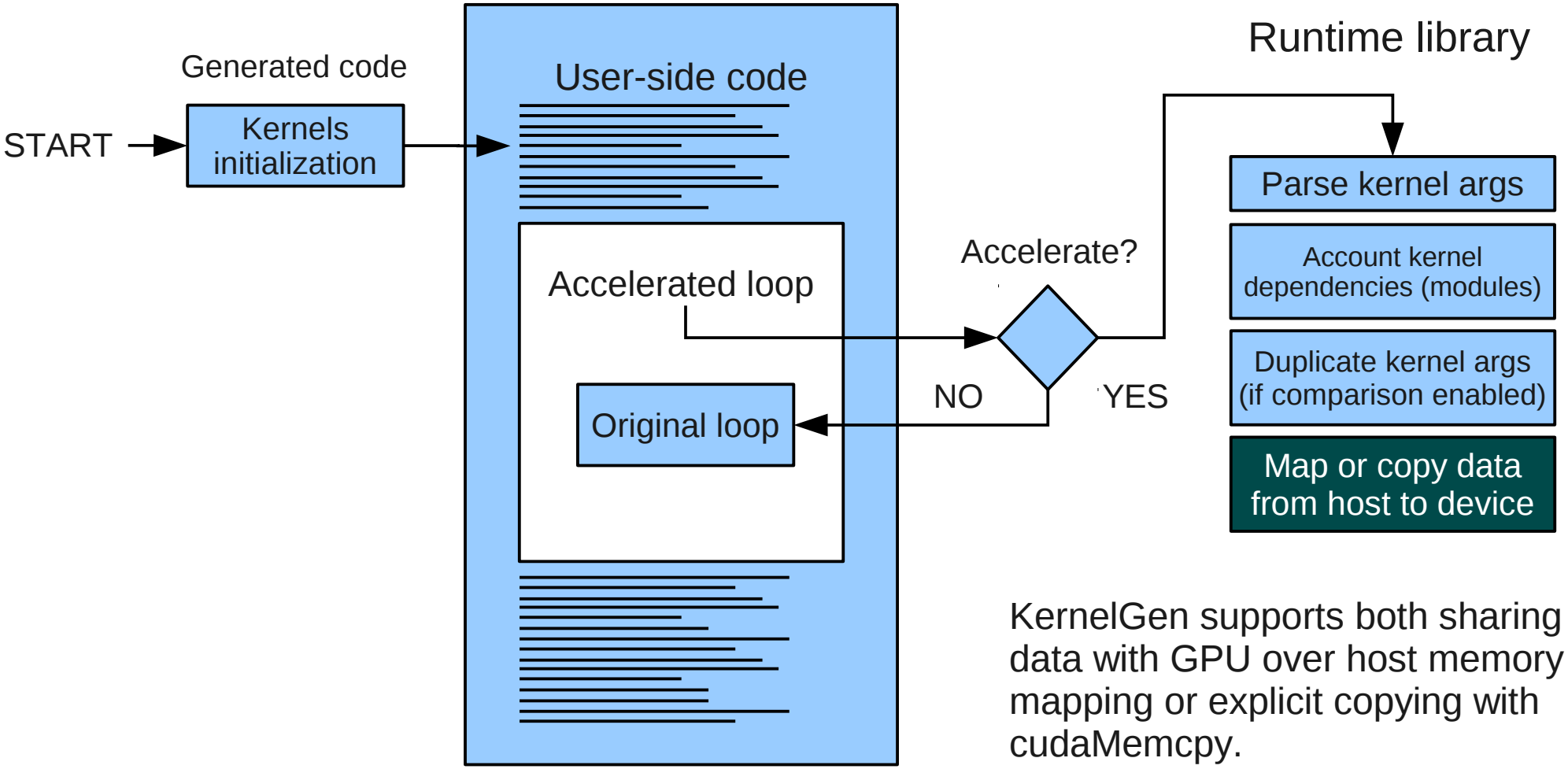
We also track kernel implicit dependencies – modules and global variables.

Runtime workflow



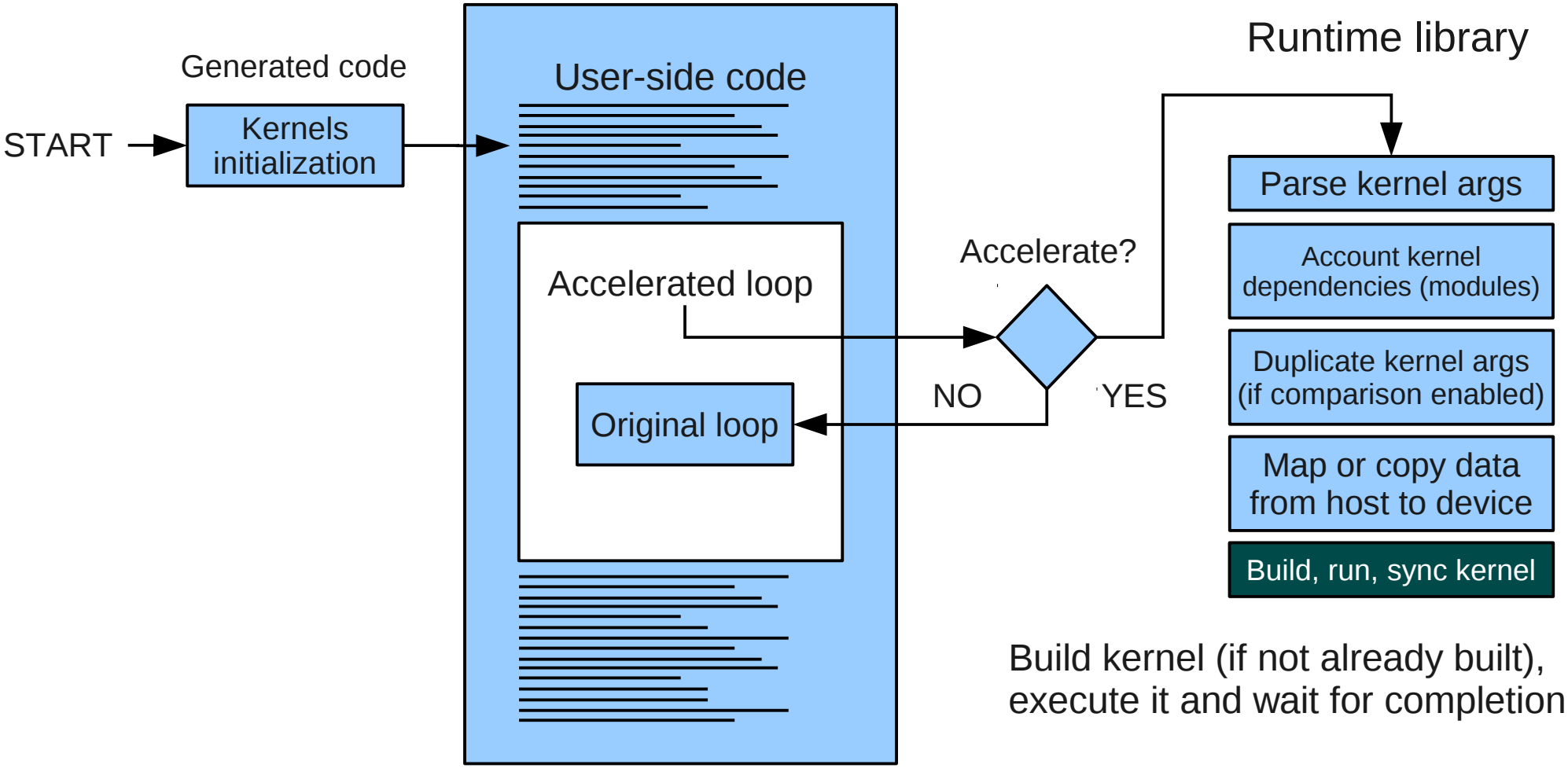
In comparison mode, kernel dependencies are duplicated to temporary arrays, and after processing results are compared to the contents of original data arrays.

Runtime workflow



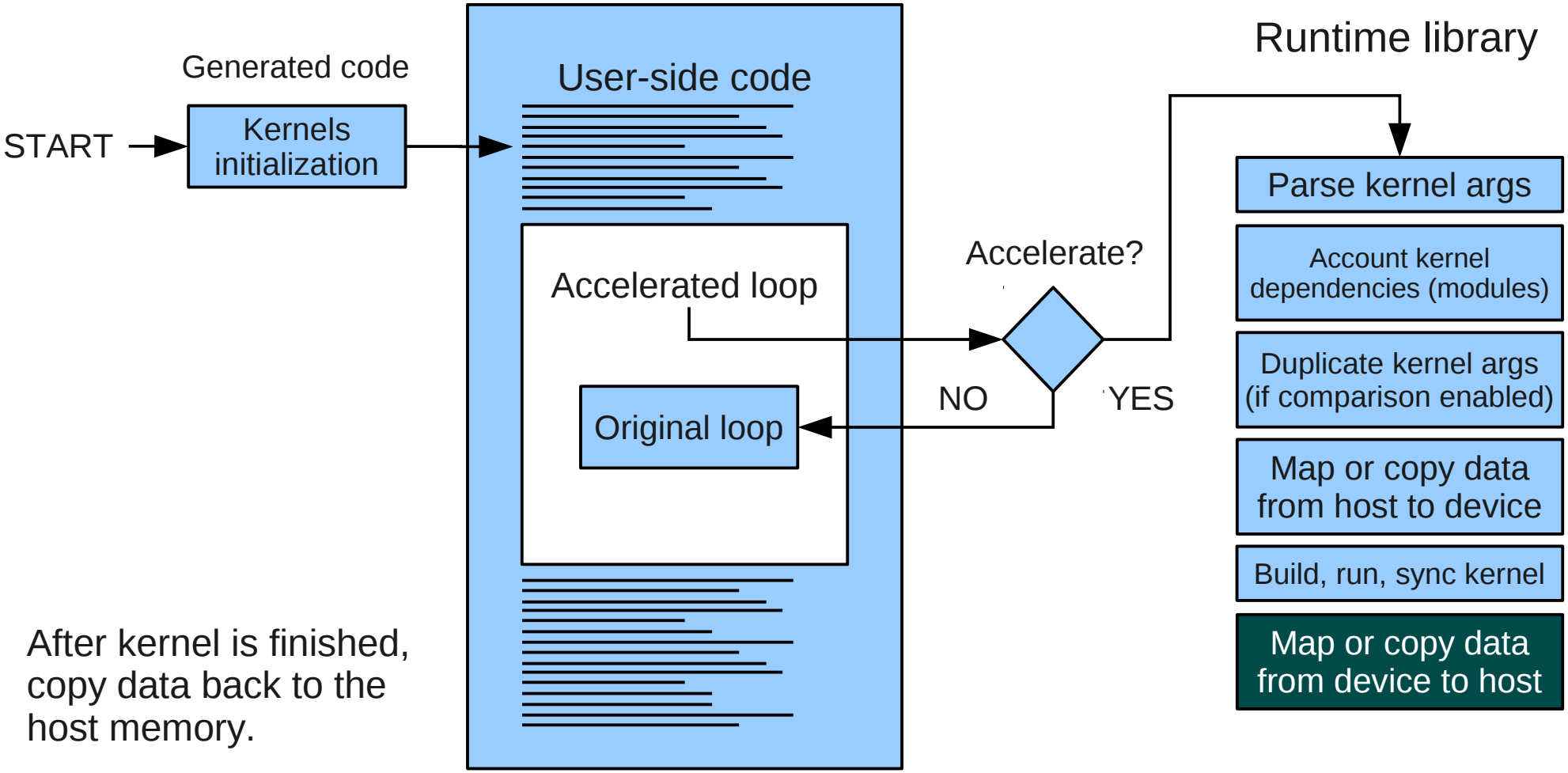
KernelGen supports both sharing data with GPU over host memory mapping or explicit copying with cudaMemcpy.

Runtime workflow



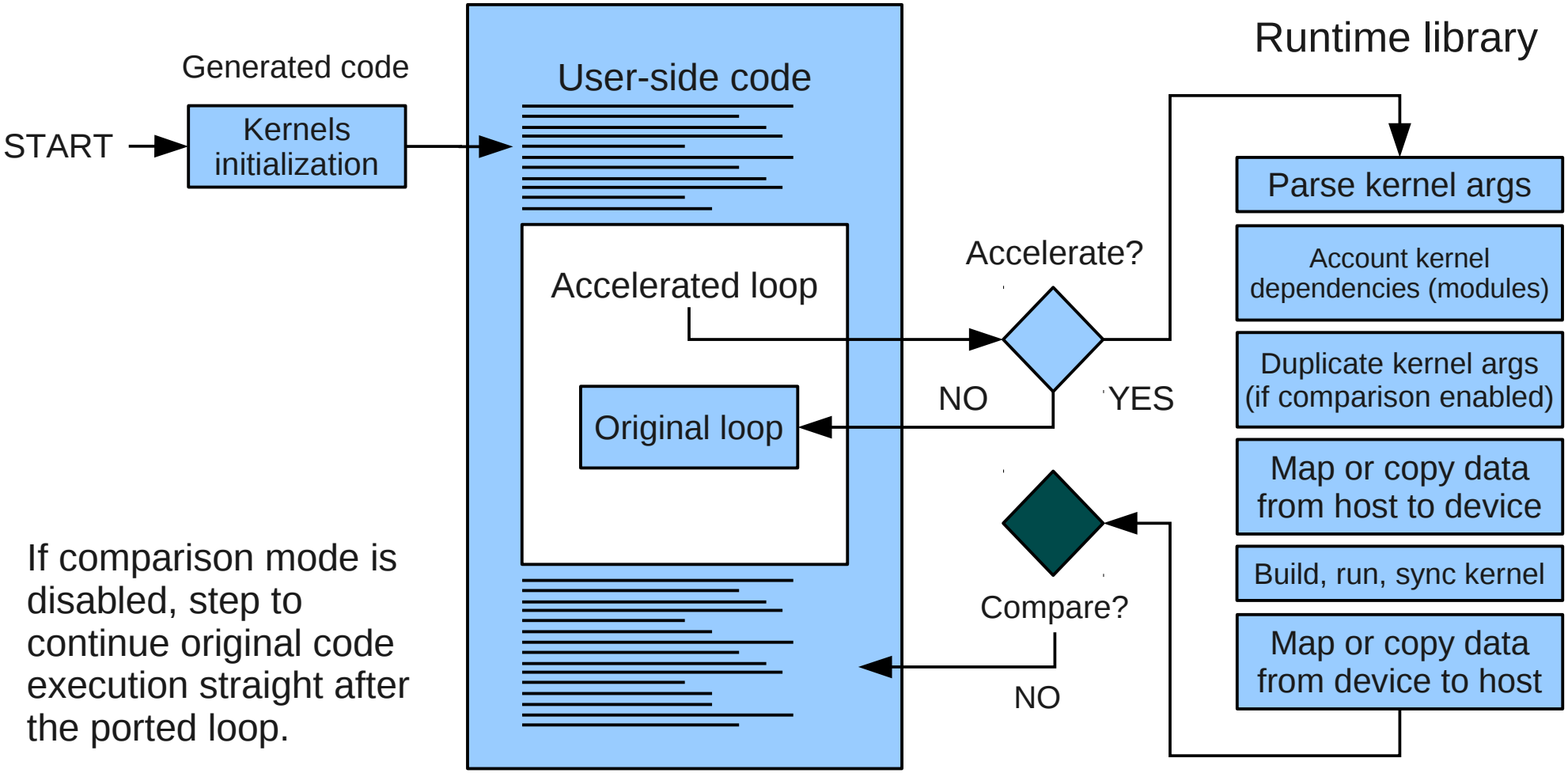
Build kernel (if not already built), execute it and wait for completion.

Runtime workflow



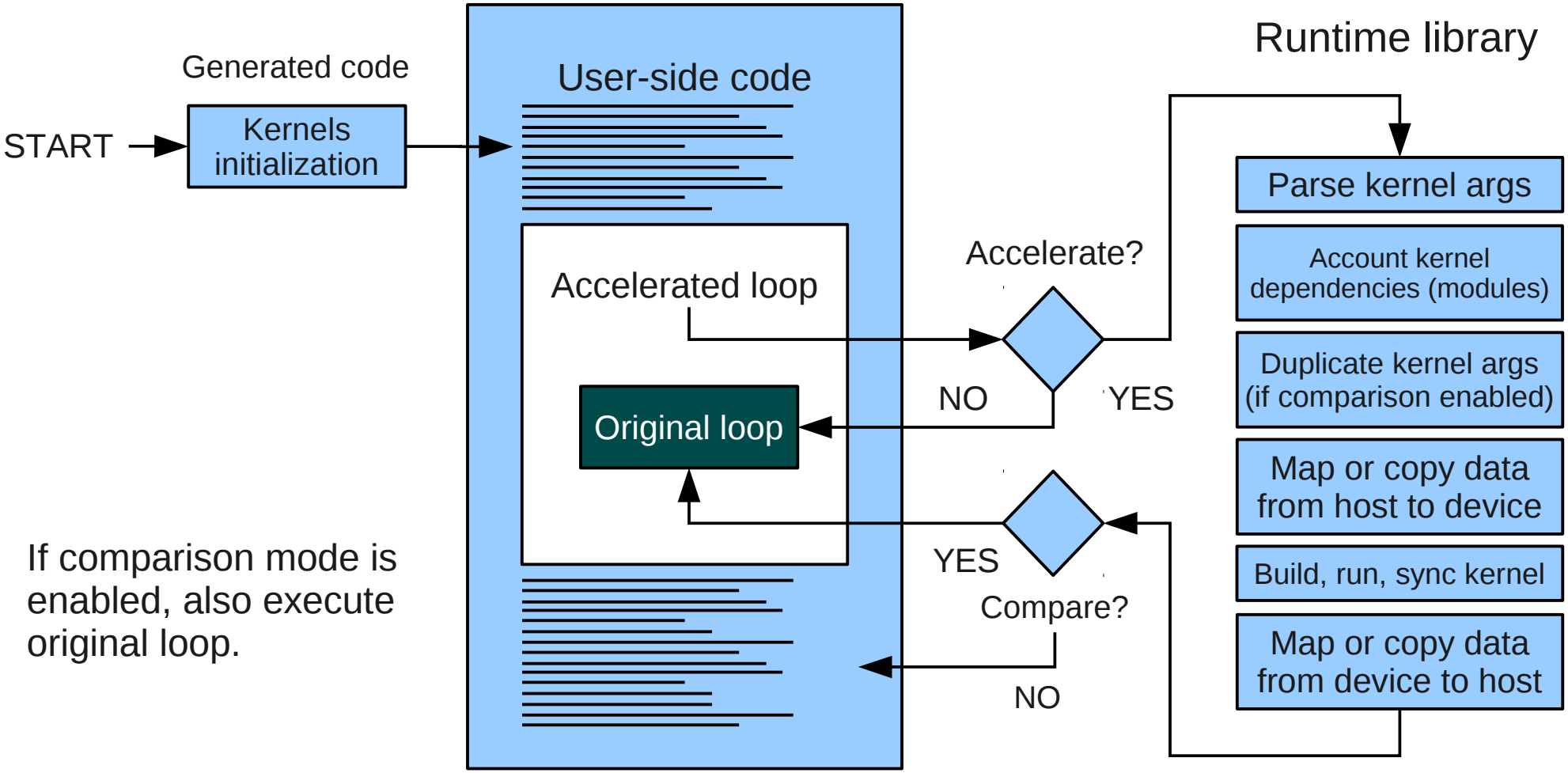
After kernel is finished, copy data back to the host memory.

Runtime workflow



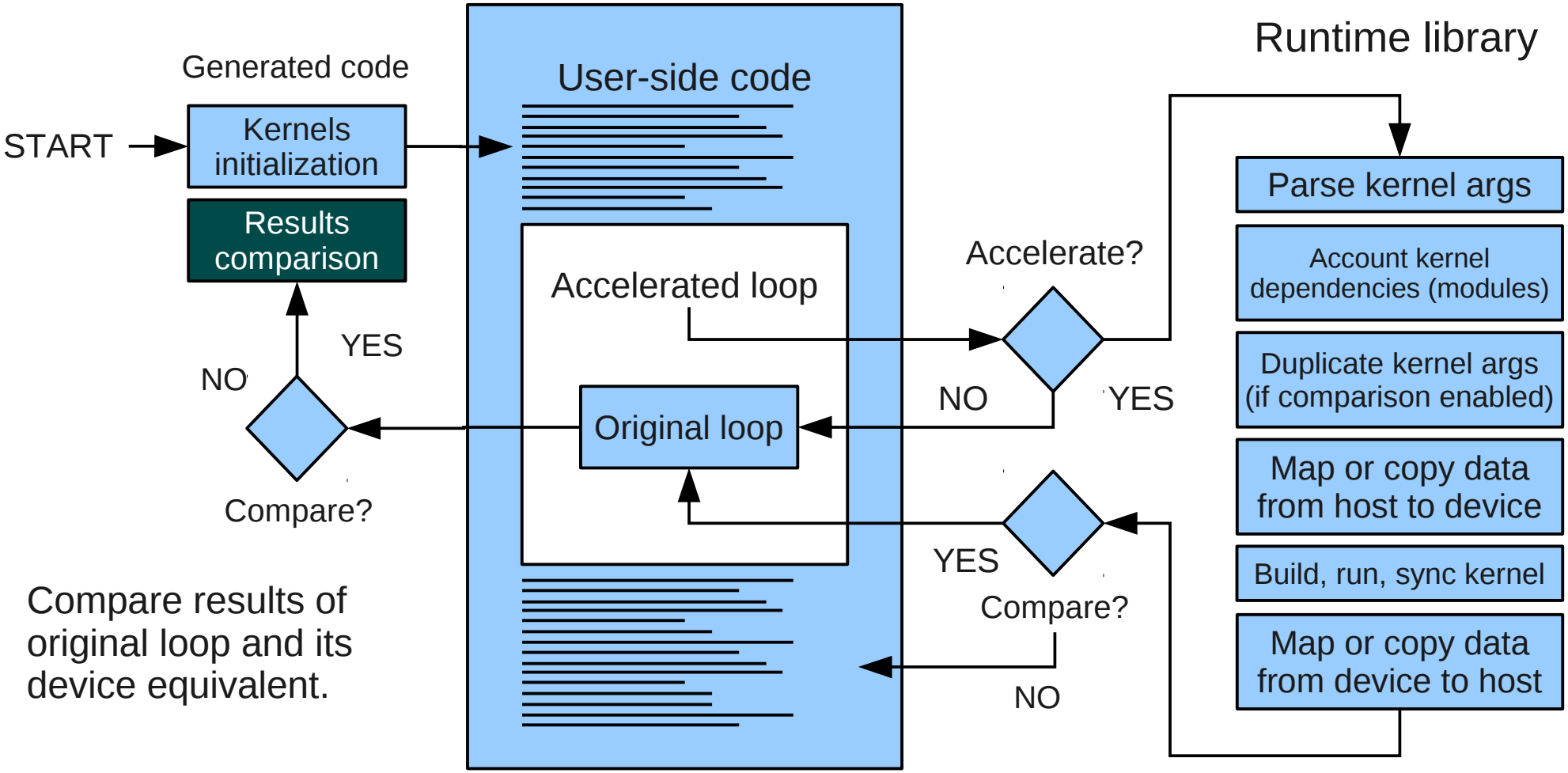
If comparison mode is disabled, step to continue original code execution straight after the ported loop.

Runtime workflow



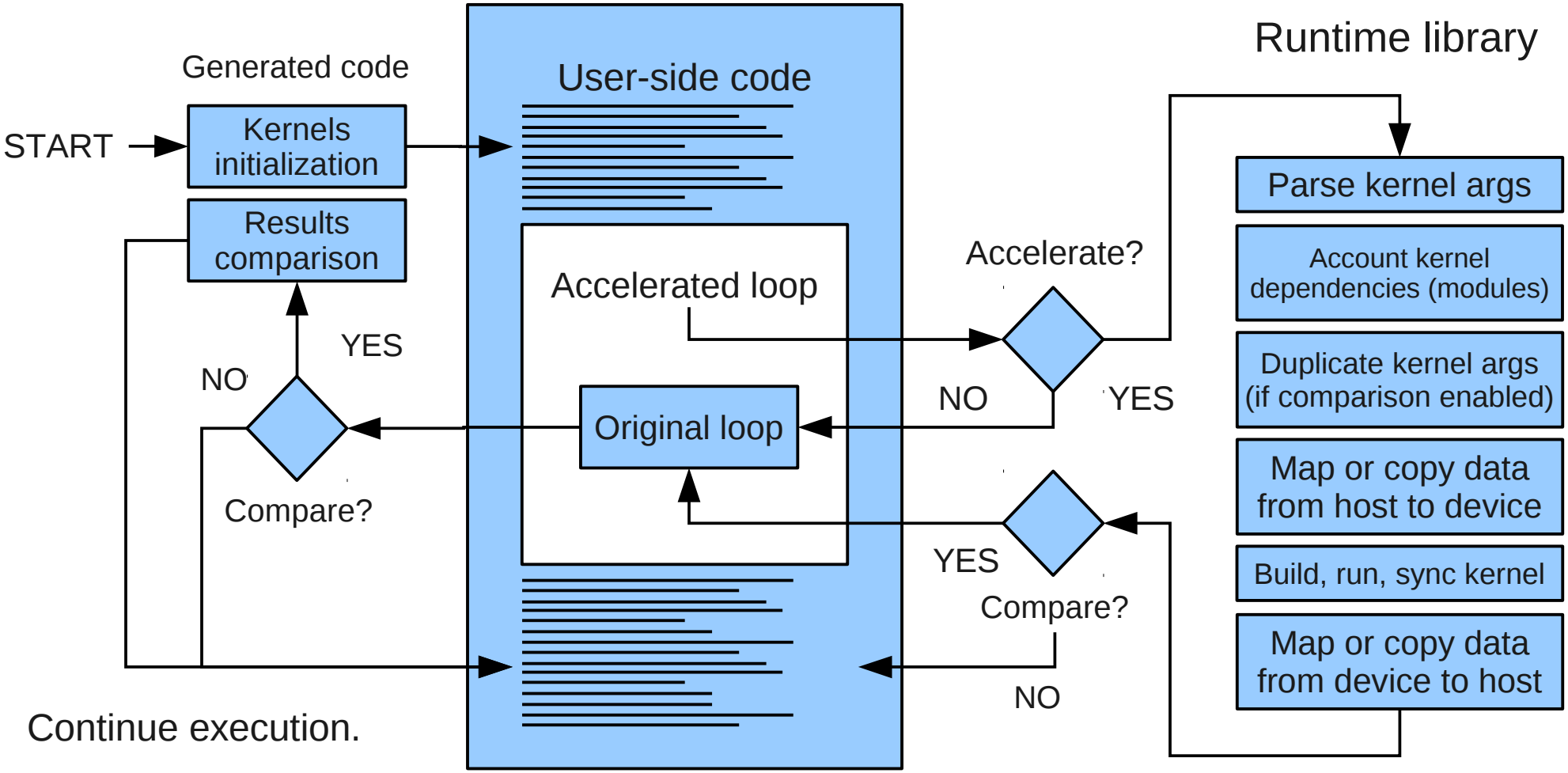
If comparison mode is enabled, also execute original loop.

Runtime workflow



Compare results of original loop and its device equivalent.

Runtime workflow

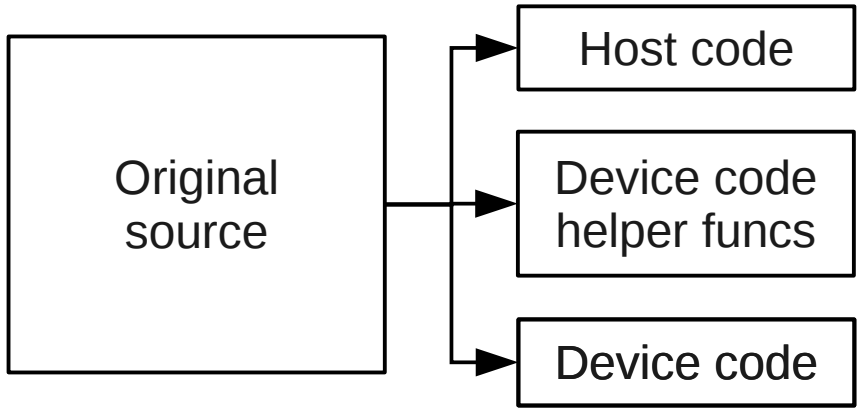


Code generation workflow

Two parts of code generation process:

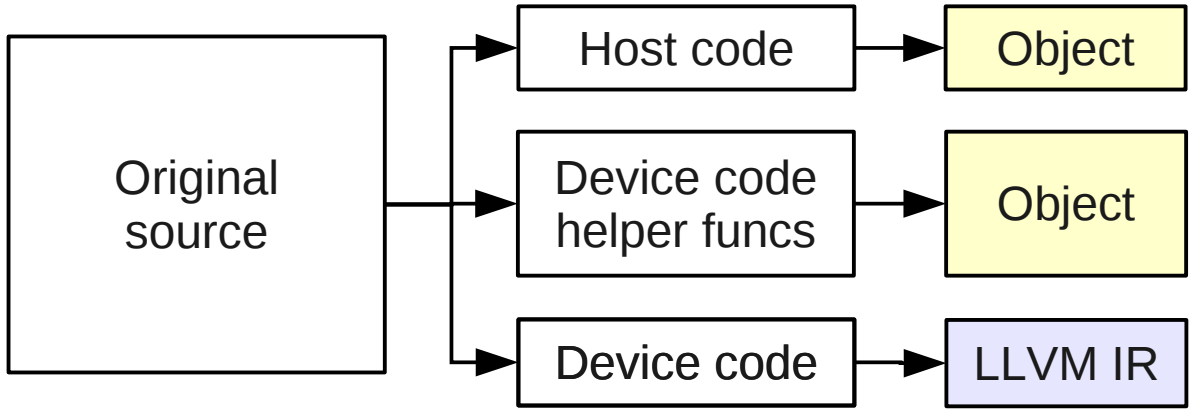
- **Compile time** – generate kernels strictly corresponding to original host loops
- **Runtime** – generate kernels, using additional info: inline external functions, optimize compute grid, etc.

Code generation workflow (compile-time part)



Loops suitable for device execution are identified in original source code, their bodies are surrounded with if-statement to switch between original loop and call to device kernel for this loop. Each suitable loop is duplicated in form of subroutine in a separate compilation unit. Additionally, helper initialization anchors are generated.

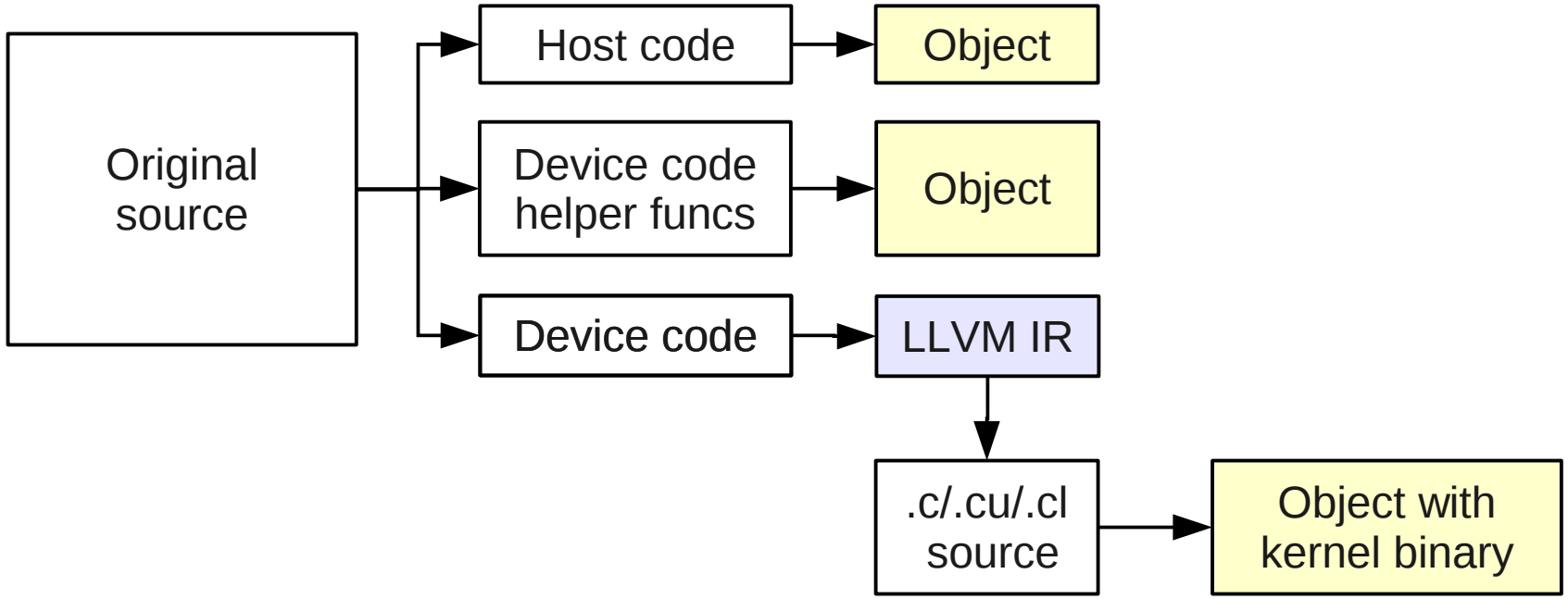
Code generation workflow (compile-time part)



Objects for host code and device code helper functions can be generated directly with CPU compiler used by application.

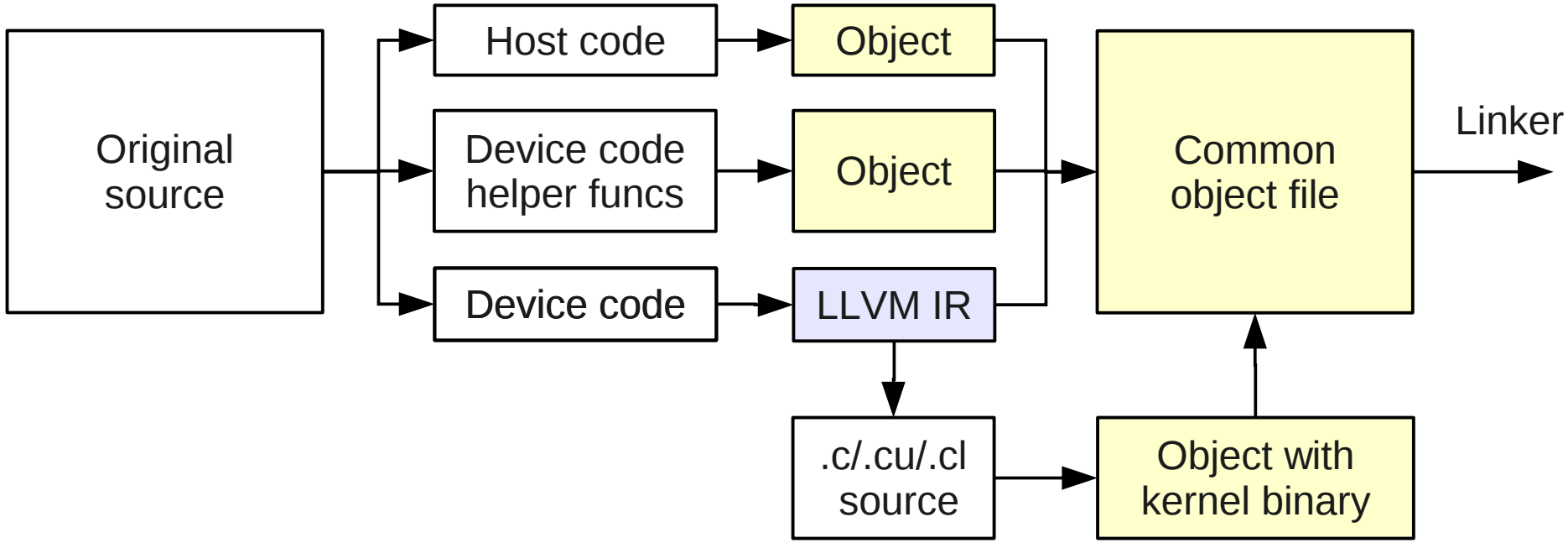
Device code is compiled into Low-Level Virtual Machine Intermediate representation (LLVM IR).

Code generation workflow (compile-time part)



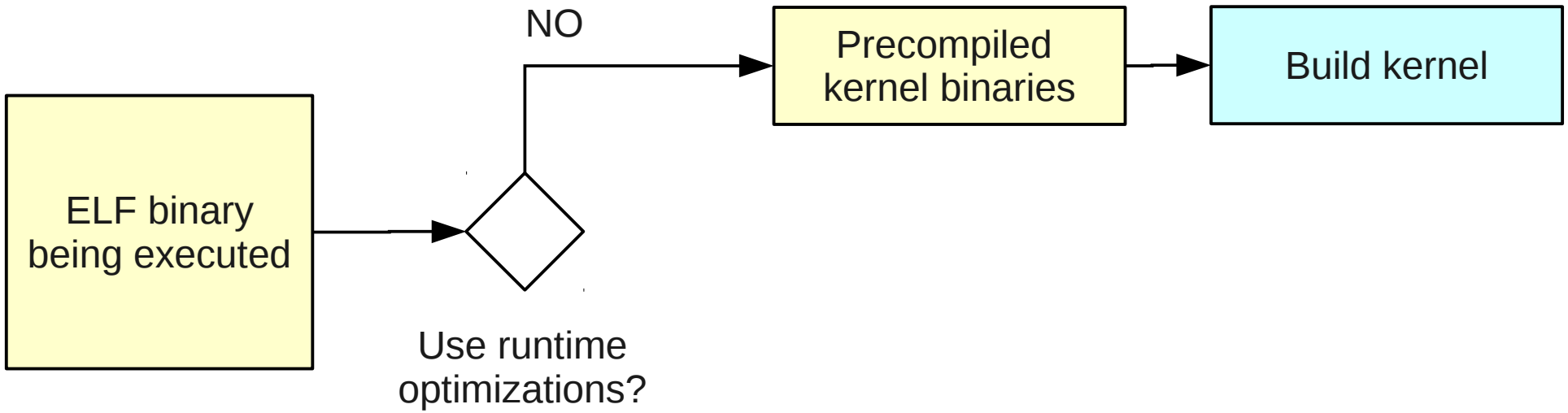
Code from LLVM IR is translated into C, CUDA or OpenCL using modified LLVM C Backend and compiled using the corresponding device compiler.

Code generation workflow (compile-time part)



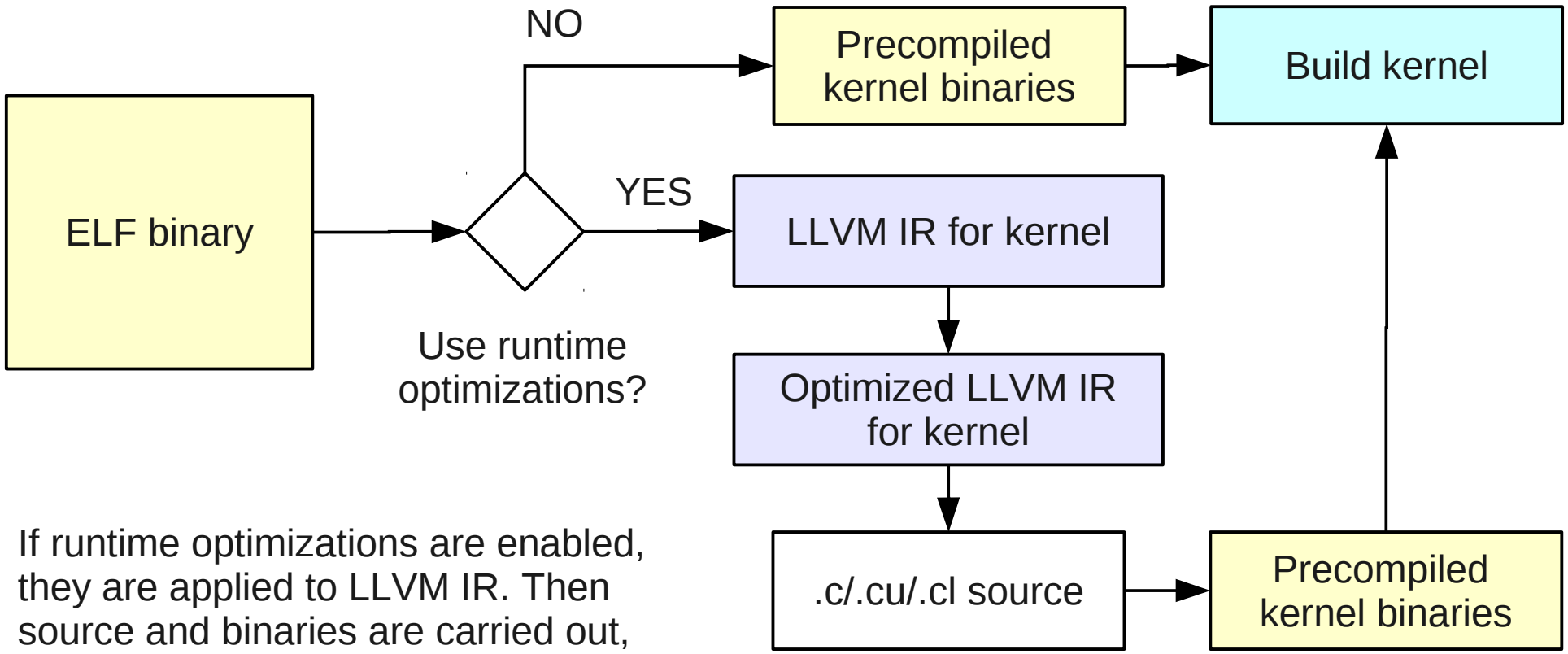
Finally, objects for all parts of the code are merged into single object to conserve "1 source → 1 object" layout. LLVM IR is also embedded into resulting object.

Code generation workflow (runtime part)



Without runtime optimizations enabled, the previously compiled kernel binary could be built and executed.

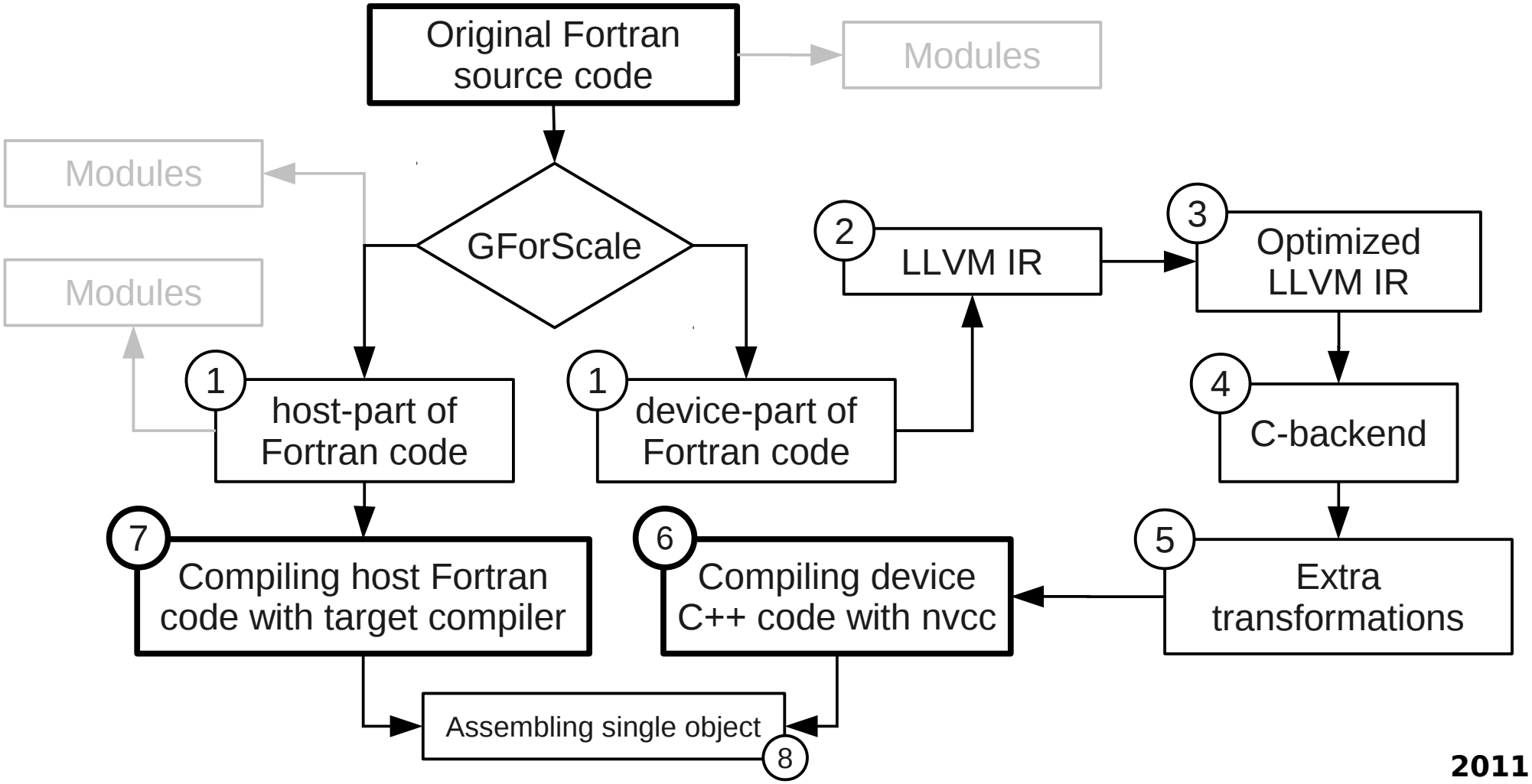
Code generation workflow (runtime part)



If runtime optimizations are enabled, they are applied to LLVM IR. Then source and binaries are carried out, just like in compile-time process.

3. Toolchain usecase

8 basic steps in total



Example: axpy

Consider toolchain steps in detail for the following simple test program:

```
subroutine axpy(n, a, x, y)

implicit none

integer, intent(in) :: n
real, intent(in) :: a, x(n)
real, intent(inout) :: y(n)

integer :: i

do i = 1, n
  y(i) = y(i) + a * x(i)
enddo

print *, 'Value of i after cycle = ', i

end subroutine axpy
```

Step 1

kgen-gforscale -Wk,--gforscale-scene-path=/opt/kgen/transforms/split/ -Wk,--gforscale-mode=tree axpy.f90

```
subroutine axpy_loop_1_gforscale(n, y, a, x)
implicit none
interface
subroutine axpy_loop_1_gforscale_blockidx_x(index, start, end)
bind(C)
use iso_c_binding
integer(c_int) :: index
integer(c_int), value :: start, end
end subroutine
subroutine axpy_loop_1_gforscale_blockidx_y(index, start, end)
bind(C)
use iso_c_binding
integer(c_int) :: index
integer(c_int), value :: start, end
end subroutine
end interface
integer :: i
integer, intent(in) :: n
real, intent(inout) :: y(n)
real, intent(in) :: a
real, intent(in) :: x(n)

#ifdef __CUDA_DEVICE_FUNC__
call axpy_loop_1_gforscale_blockidx_x(i, 1, n)
#else
do i = 1, n
#endif

  y(i) = y(i) + a * x(i)

#ifndef __CUDA_DEVICE_FUNC__
enddo
#endif

end subroutine axpy_loop_1_gforscale
```

device-code

```
subroutine axpy(n, a, x, y)
USE GFORSCALE


implicit none

integer, intent(in) :: n
real, intent(in) :: a, x(n)
real, intent(inout) :: y(n)

integer :: i


!$GFORSCALE SELECT axpy_loop_1_gforscale
if (gforscale_select(0, 1, 'axpy' // char(0))) then
!$GFORSCALE CALL axpy_loop_1_gforscale
#ifdef __CUDA_DEVICE_FUNC__
  call gforscale_launch('axpy_loop_1_gforscale_' // char(0), &
    1, n, 0, 0, 4, n, sizeof(n), y, sizeof(y), a, sizeof(a), x, sizeof(x))
i = n + 1
#else
  call axpy_loop_1_gforscale(n, y, a, x)
#endif
!$GFORSCALE END CALL axpy_loop_1_gforscale
else
!$GFORSCALE LOOP axpy_loop_1_gforscale
do i = 1, n
  y(i) = y(i) + a * x(i)
enddo
!$GFORSCALE END LOOP axpy_loop_1_gforscale
endif
!$GFORSCALE END SELECT axpy_loop_1_gforscale

print *, 'Value of i after cycle = ', i

end subroutine axpy
```

host-code

Step 2

dragonegg-gfortran -c axpy.axpy_loop_1_gforscale.F90 -D__CUDA_DEVICE_FUNC__ -ffree-line-length-none -fplugin=/opt/llvm/dragonegg/lib64/dragonegg.so -O0 -S -fplugin-arg-dragonegg-emit-ir -o axpy.axpy_loop_1_gforscale.F90.bc

```
; ModuleID = 'axpy.axpy_loop_1_gforscale.F90'
target datalayout = "e-p:64:64:64-i1:8:8-i8:8:8-i16:16:16-i32:32:32-
i64:64:64-f32:32:32-f64:64:64-v64:64:64-v128:128:128-a0:0:64-s0:64:64-
f80:128:128-f128:128:128-n8:16:32:64"
target triple = "x86_64-unknown-linux-gnu"

module asm "\09.ident\09\22GCC: (GNU) 4.5.4 20110527 (prerelease) LLVM:
131968\22"

%"integer(kind=4)" = type i32
%"real(kind=4)" = type float

define void @axpy_loop_1_gforscale_(i32* %n, [0 x float]* %y, float* %a, [0
x float]* %x) nounwind {
entry:
  %n_addr = alloca i32*, align 8
  %y_addr = alloca [0 x float]*, align 8
  %a_addr = alloca float*, align 8
  %x_addr = alloca [0 x float]*, align 8
  %memtmp = alloca i32
  %"alloca point" = bitcast i32 0 to i32
  store i32* %n, i32** %n_addr
  store [0 x float]* %y, [0 x float]** %y_addr
  store float* %a, float** %a_addr
  store [0 x float]* %x, [0 x float]** %x_addr
  %0 = load i32** %n_addr, align 64
  %1 = load [0 x float]** %y_addr, align 64
  %2 = load float** %a_addr, align 64
  %3 = load [0 x float]** %x_addr, align 64
  %"ssa point" = bitcast i32 0 to i32
  br label %"2"

"2":                                              ; preds = %entry
  %4 = load i32* %0, align 4
  %5 = sext i32 %4 to i64
  %6 = icmp sge i64 %5, 0
  %7 = select i1 %6, i64 %5, i64 0
  %8 = add nsw i64 %7, -1
  %9 = mul i64 %7, 32
  %10 = mul i64 %7, 4
  %11 = load i32* %0, align 4
  %12 = sext i32 %11 to i64
  %13 = icmp sge i64 %12, 0
  %14 = select i1 %13, i64 %12, i64 0
  %15 = add nsw i64 %14, -1
  %16 = mul i64 %14, 32
  %17 = mul i64 %14, 4
  %18 = load i32* %0, align 4
  call void (i32*, i32, i32, ...)* @axpy_loop_1_gforscale_blockidx_x(i32*
noalias %memtmp, i32 1, i32 %18) nounwind
  %19 = load i32* %memtmp, align 4
  %20 = sext i32 %19 to i64
  %21 = add nsw i64 %20, -1
  %22 = load i32* %memtmp, align 4
  %23 = sext i32 %22 to i64
  %24 = add nsw i64 %23, -1
  %25 = bitcast [0 x float]* %1 to float*
  %26 = getelementptr float* %25, i64 %24
  %27 = load float* %26, align 4
  %28 = load float* %2, align 4
  %29 = load i32* %memtmp, align 4
  %30 = sext i32 %29 to i64
  %31 = add nsw i64 %30, -1
  %32 = bitcast [0 x float]* %3 to float*
  %33 = getelementptr float* %32, i64 %31
  %34 = load float* %33, align 4
  %35 = fmul float %28, %34
  %36 = fadd float %27, %35
  %37 = bitcast [0 x float]* %1 to float*
  %38 = getelementptr float* %37, i64 %21
  store float %36, float* %38, align 4
  br label %return

return:                                           ; preds = %"2"
  ret void
}

declare void @axpy_loop_1_gforscale_blockidx_x(i32* noalias, i32, i32, ...)
```

Step 3

/opt/llvm/bin/opt -std-compile-opts axpy.axpy_loop_1_gforscale.F90.bc -S -o axpy.axpy_loop_1_gforscale.F90.bc.opt

```
; ModuleID = 'axpy.axpy_loop_1_gforscale.F90.bc'
target datalayout = "e-p:64:64:64-i1:8:8-i8:8:8-i16:16:16-i32:32:32-i64:64:64-f32:32:32-f64:64:64-v64:64:64-v128:128:128-a0:0:64-
s0:64:64-f80:128:128-f128:128:128-n8:16:32:64"
target triple = "x86_64-unknown-linux-gnu"

module asm "\09.ident\09\22GCC: (GNU) 4.5.4 20110527 (prerelease) LLVM: 131968\22"

define void @axpy_loop_1_gforscale_(i32* nocapture %n, [0 x float]* nocapture %y, float* %a, [0 x float]* %x) nounwind {
entry:
  %memtmp = alloca i32, align 4
  %0 = load i32* %n, align 4
  call void (i32*, i32, i32, ...)* @axpy_loop_1_gforscale_blockidx_x(i32* noalias %memtmp, i32 1, i32 %0) nounwind
  %1 = load i32* %memtmp, align 4
  %2 = sext i32 %1 to i64
  %3 = add nsw i64 %2, -1
  %4 = getelementptr [0 x float]* %y, i64 0, i64 %3
  %5 = load float* %4, align 4
  %6 = load float* %a, align 4
  %7 = getelementptr [0 x float]* %x, i64 0, i64 %3
  %8 = load float* %7, align 4
  %9 = fmul float %6, %8
  %10 = fadd float %5, %9
  store float %10, float* %4, align 4
  ret void
}

declare void @axpy_loop_1_gforscale_blockidx_x(i32* noalias, i32, i32, ...)
```

Step 4

/opt/llvm/bin/llc -march=c axpy.axpy_loop_1_gforscale.F90.bc.opt
-o axpy.axpy_loop_1_gforscale.F90.bc.cu

```
asm("\t.ident\t\"GCC: (GNU) 4.5.4 20110527 (prerelease) LLVM: 131968\"\n"
"");

...

#ifdef __CUDA_DEVICE_FUNC__
__device__
#endif
void axpy_loop_1_gforscale_(unsigned int *llvm_cbe_n, struct l_unnamed0 (*llvm_cbe_y), float *llvm_cbe_a, struct l_unnamed0 (*llvm_cbe_x));
#ifdef __CUDA_DEVICE_FUNC__
__device__
#endif
void axpy_loop_1_gforscale_blockidx_x(unsigned int *, unsigned int , unsigned int );

void axpy_loop_1_gforscale_(unsigned int *llvm_cbe_n, struct l_unnamed0 (*llvm_cbe_y), float *llvm_cbe_a, struct l_unnamed0 (*llvm_cbe_x)) {
  unsigned int llvm_cbe_memtmp;    /* Address-exposed local */
  unsigned int llvm_cbe_tmp__1;
  unsigned int llvm_cbe_tmp__2;
  unsigned long long llvm_cbe_tmp__3;
  float *llvm_cbe_tmp__4;
  float llvm_cbe_tmp__5;
  float llvm_cbe_tmp__6;
  float llvm_cbe_tmp__7;

  llvm_cbe_tmp__1 = *llvm_cbe_n;
  axpy_loop_1_gforscale_blockidx_x((&llvm_cbe_memtmp), 1u, llvm_cbe_tmp__1);
  llvm_cbe_tmp__2 = *(&llvm_cbe_memtmp);
  llvm_cbe_tmp__3 = ((unsigned long long )(((unsigned long long )(((signed long long )(signed int )llvm_cbe_tmp__2))) + ((unsigned long long )
18446744073709551615ull)));
  llvm_cbe_tmp__4 = (&(*llvm_cbe_y).array[((signed long long )llvm_cbe_tmp__3)]);
  llvm_cbe_tmp__5 = *llvm_cbe_tmp__4;
  llvm_cbe_tmp__6 = *llvm_cbe_a;
  llvm_cbe_tmp__7 = *((&(*llvm_cbe_x).array[((signed long long )llvm_cbe_tmp__3)]));
  *llvm_cbe_tmp__4 = (((float )(llvm_cbe_tmp__5 + (((float )(llvm_cbe_tmp__6 * llvm_cbe_tmp__7))))));
  return;
}
```

Step 5

```
asm("\t.ident\t\"GCC: (GNU) 4.5.4 20110527 (prerelease) LLVM: 131968 \"\n"
"");

...

#ifdef __CUDA_DEVICE_FUNC__
extern "C" __global__
#endif
void axpy_loop_1_gforscale_( unsigned int *llvm_cbe_n, struct l_unnamed0 (*llvm_cbe_y), float *llvm_cbe_a, struct l_unnamed0 (*llvm_cbe_x));
#ifdef __CUDA_DEVICE_FUNC__
__device__
#endif
void axpy_loop_1_gforscale_blockidx_x( unsigned int* index, unsigned int start, unsigned int end) { *index = blockIdx.x + start; }

void axpy_loop_1_gforscale_( unsigned int *llvm_cbe_n, struct l_unnamed0 (*llvm_cbe_y), float *llvm_cbe_a, struct l_unnamed0 (*llvm_cbe_x)) {
  unsigned int llvm_cbe_memtmp;    /* Address-exposed local */
  unsigned int llvm_cbe_tmp__1;
  unsigned int llvm_cbe_tmp__2;
  unsigned long long llvm_cbe_tmp__3;
  float *llvm_cbe_tmp__4;
  float llvm_cbe_tmp__5;
  float llvm_cbe_tmp__6;
  float llvm_cbe_tmp__7;

  llvm_cbe_tmp__1 = *llvm_cbe_n;
  axpy_loop_1_gforscale_blockidx_x((&llvm_cbe_memtmp),  1u, llvm_cbe_tmp__1);
  llvm_cbe_tmp__2 = *(&llvm_cbe_memtmp);
  llvm_cbe_tmp__3 = (( unsigned long long )(((unsigned long long )(((signed long long )(signed int )llvm_cbe_tmp__2))) + (( unsigned long long )
18446744073709551615ull )));
  llvm_cbe_tmp__4 = (&(*llvm_cbe_y).array[(( signed long long )llvm_cbe_tmp__3)]);
  llvm_cbe_tmp__5 = *llvm_cbe_tmp__4;
  llvm_cbe_tmp__6 = *llvm_cbe_a;
  llvm_cbe_tmp__7 = *((&(*llvm_cbe_x).array[(( signed long long )llvm_cbe_tmp__3)]));
  *llvm_cbe_tmp__4 = ((( float )(llvm_cbe_tmp__5 + ((( float )(llvm_cbe_tmp__6 * llvm_cbe_tmp__7))))));
  return;
}
```

Steps 6-8

Final compilation of host and device parts, assembling into single object file:

```
# 6
nvcc -g -c axpy.axpy_loop_1_gforscale.F90.bc.cu -D__CUDA_DEVICE_FUNC__ -G -o
axpy.axpy_loop_1_gforscale.F90.o

# 7
gfortran -g -c axpy.host.F90 -D__CUDA_DEVICE_FUNC__ -ffree-line-length-none
-I/opt/kgen/include -o axpy.host.F90.o

# 8
/usr/bin/ld --unresolved-symbols=ignore-all -r -o axpy.o_kgen axpy.host.F90.o
axpy.axpy_loop_1_gforscale.F90.o
```

Testing axpy

 # By default – execute on CPU

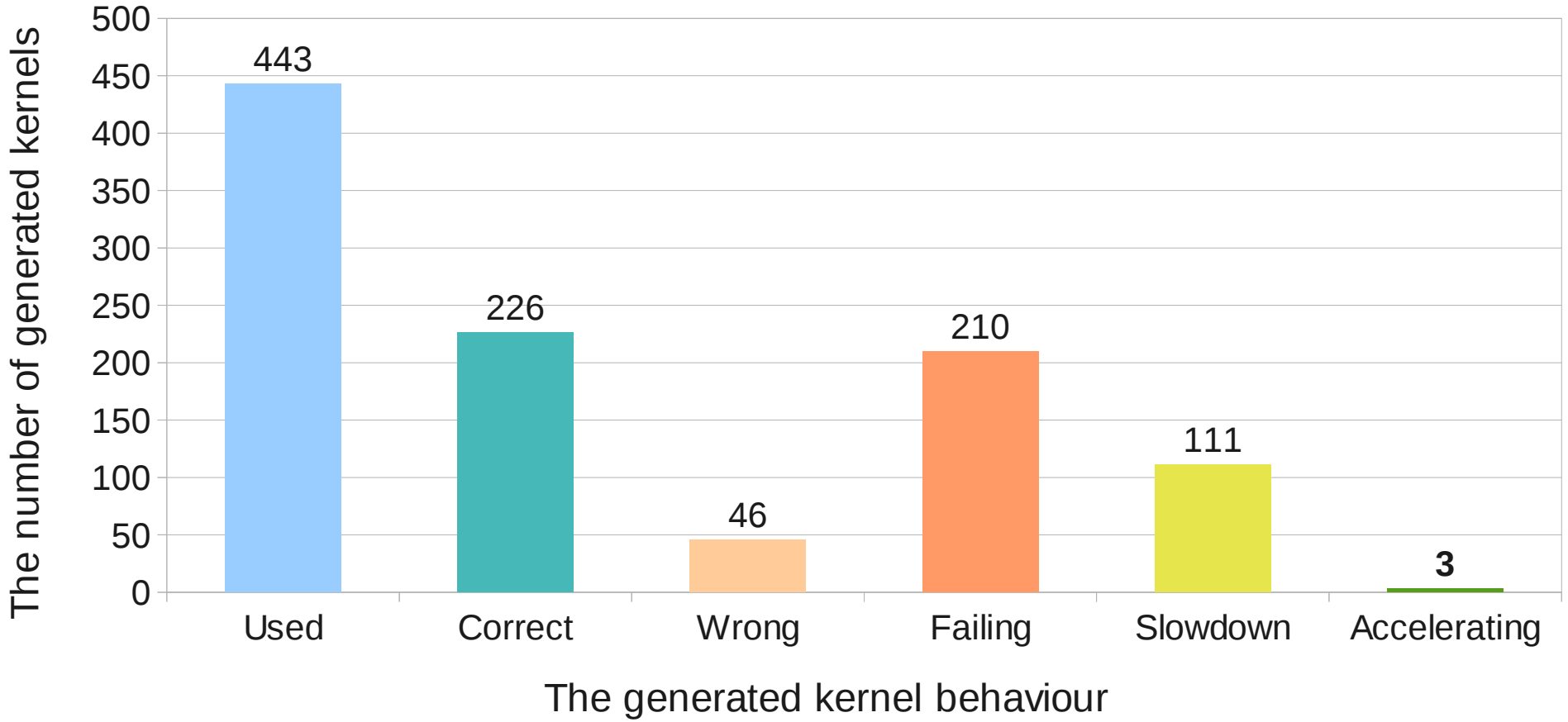
```
[marcusmae@T61p axpy]$ ./axpy
Usage: ./axpy <n> <eps>
[marcusmae@T61p axpy]$ ./axpy 10 0.001
 Value of i after cycle =           11
Max abs diff = 0.000000
```

 # Use GPU kernel if the corresponding environment variable set to 1
 # (extra debug output showing how arguments are mapped into device memory)

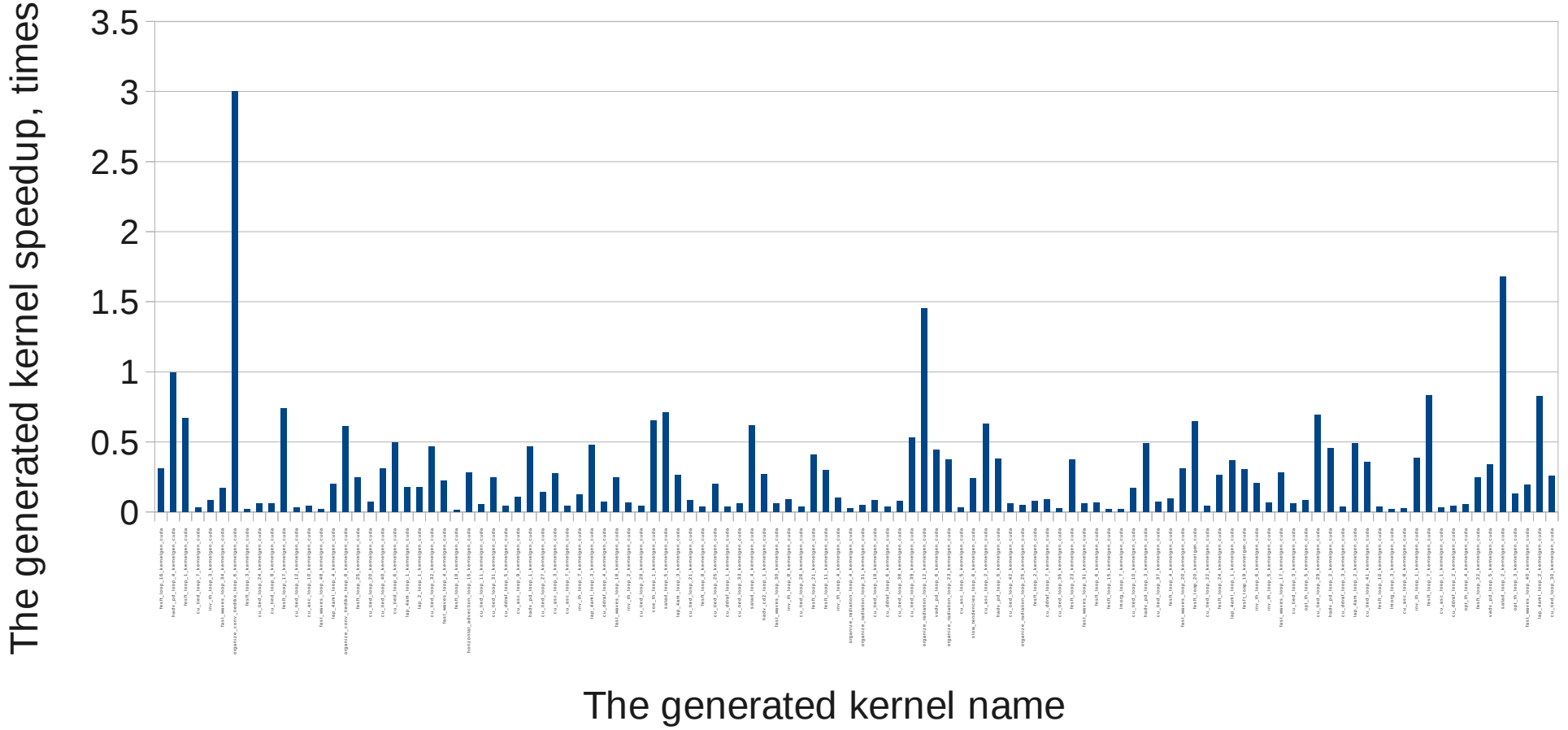
```
[marcusmae@T61p axpy]$ axpy_1=1 ./axpy 1000 0.001
arg 0 maps memory segment [140735344500736 .. 140735344508928] to
[1052672 .. 1060864]
arg 1 maps memory segment [28172288 .. 28184576] to [1060864 .. 1073152]
arg 2 reuses mapping created by arg 0
arg 3 reuses mapping created by arg 1
 Value of i after cycle =         1001
Max abs diff = 0.000000
```

4. Testing unoptimized generator

COSMO – coverage

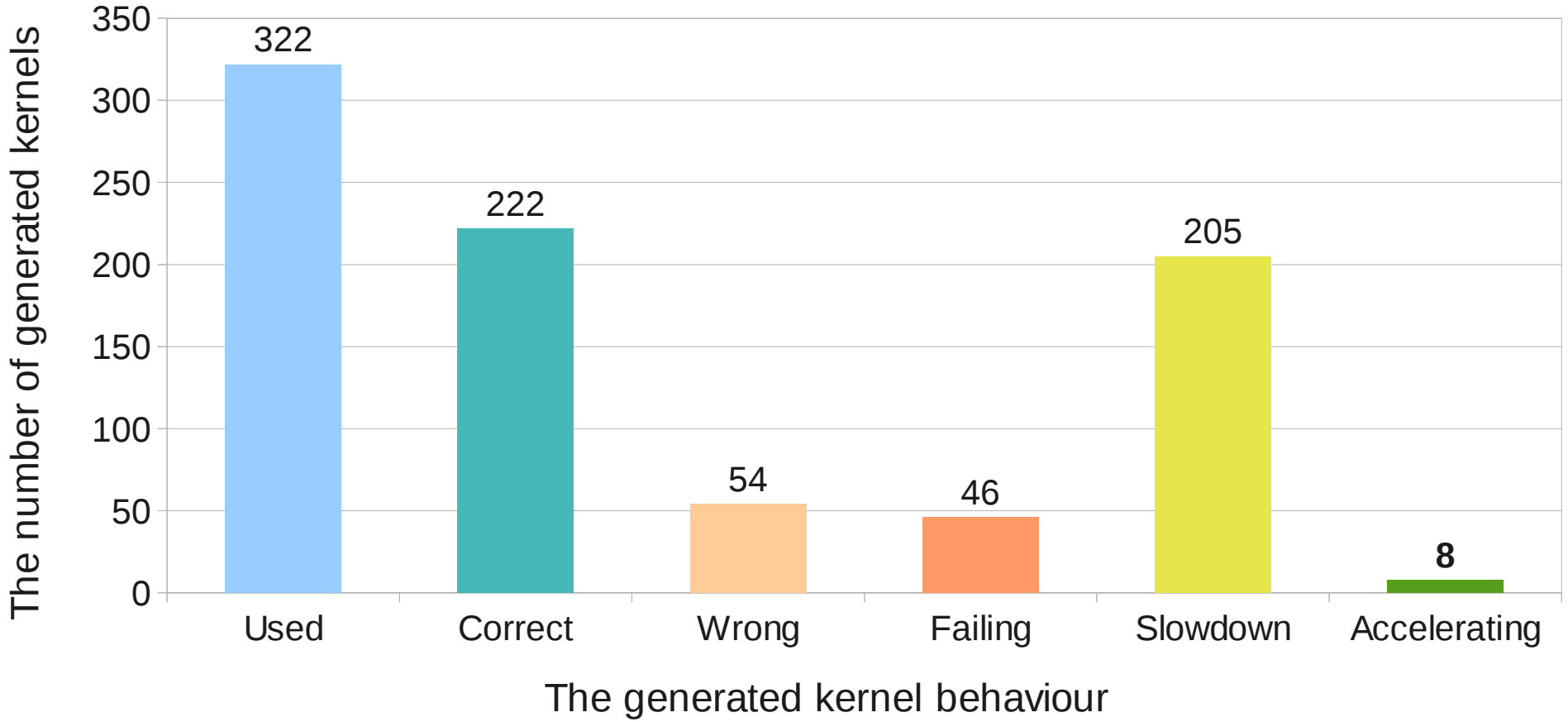


COSMO – performance

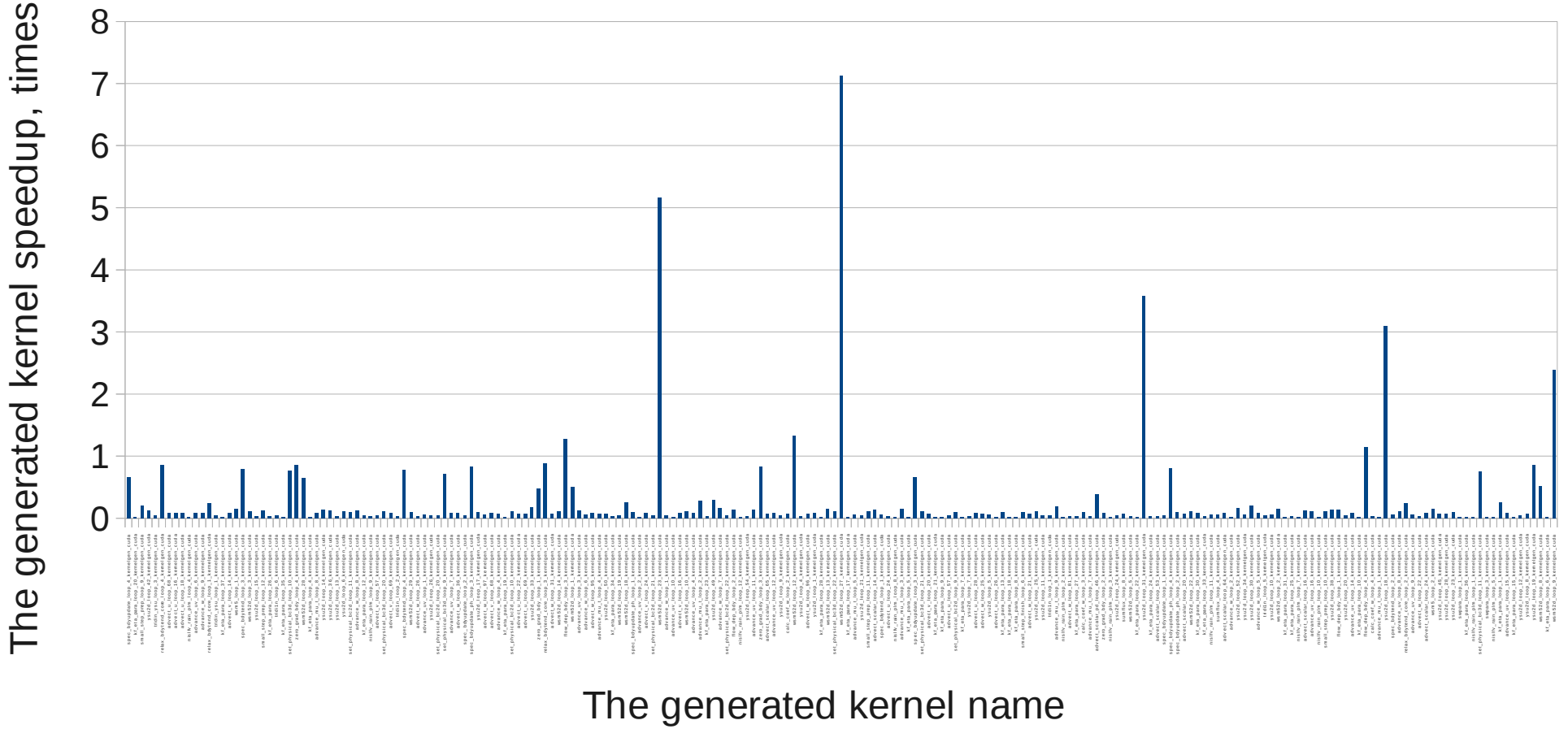


2011

WRF – coverage



WRF – performance



6. Development schedule

Stage 1 (April - June)

- Put together all necessary toolchain parts, write the main script
- Test C code generation, file bugs to llvm, patch C backend for CUDA support
- Complete existing host-device code split transform (previously started in 2009 for CellBE)
- Implement kernel invocation runtime
- Implement kernel self-checking runtime
- Compile COSMO with toolchain and present charts showing the percentage of successfully generated kernels with checked correct results

Stage 2 (July - October)

- Improve support/coverage
- Improve efficiency
- Compare performance with other generation tools
- Present the work and carefully listen to feedback

Stage 2 (July - October)

- Improve support/coverage
  - More testing on COSMO and other models, file bugs (+2 RHM fellows)
  - Fix the most hot bugs in host-device code split transform
  - Use Polly/Pluto for more accurate capable loops recognition
  - Support link-time generation for kernels with external dependencies
- Improve efficiency
  - Use shared memory in stencils (+1 contractor)
  - Implement both zero-copy and active data synchronization modes
  - Kernel invocation configs caching
  - [variant] Consider putting serial code into single GPU thread as well, to have the whole model instance running on GPU
  - [variant] Consider selective/prioritized data synchronization support, using data dependencies lookup
  - [variant, suggested by S.K.] CPU ↔ GPU work sharing inside MPI process
- Compare performance with other generation tools
- Present the work and carefully listen to feedback

5. Team & resources

Team

Artem Petrov	(testing, coordination)
Dr Yulia Martynova	(WRF testing)

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Dmitry Mikushin	(development, planning)

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Support from communities:

LLVM

Polly/LLVM

gcc/gfortran

Toolchain installation

/opt/kgen/

- bin/
  - g95xml-refids, g95xml-tree } Source code XML-markup
  - kgen } Script performing steps 1-8
  - kgen-gforscale } Source-to-source translator
  - kgen-gfortran } **Frontend (“compiler”)**
- include/
  - gforscale.h
  - gforscale.mod, gforscale.dragonegg.mod } Runtime-modules
- lib/
  - libgforscale.so } Runtime-library
- transforms/
  - split/ } Tree of code transformation rules performing host/device code split