

MLIR-based offline memory planning and other graph-level optimisations for xcore.ai

Deepak Panickal Laszlo Kindrat*(Modular) Scott Roset

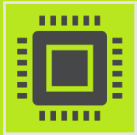


EXTERNAL – PUBLIC
©2023 XMOS Ltd.

May-23

*Work done while
at XMOS

BACKGROUND



xcore.ai is a high performance, low latency microcontroller, with 16 logical cores split between two multithreaded processor 'tiles', each with 512KB of SRAM

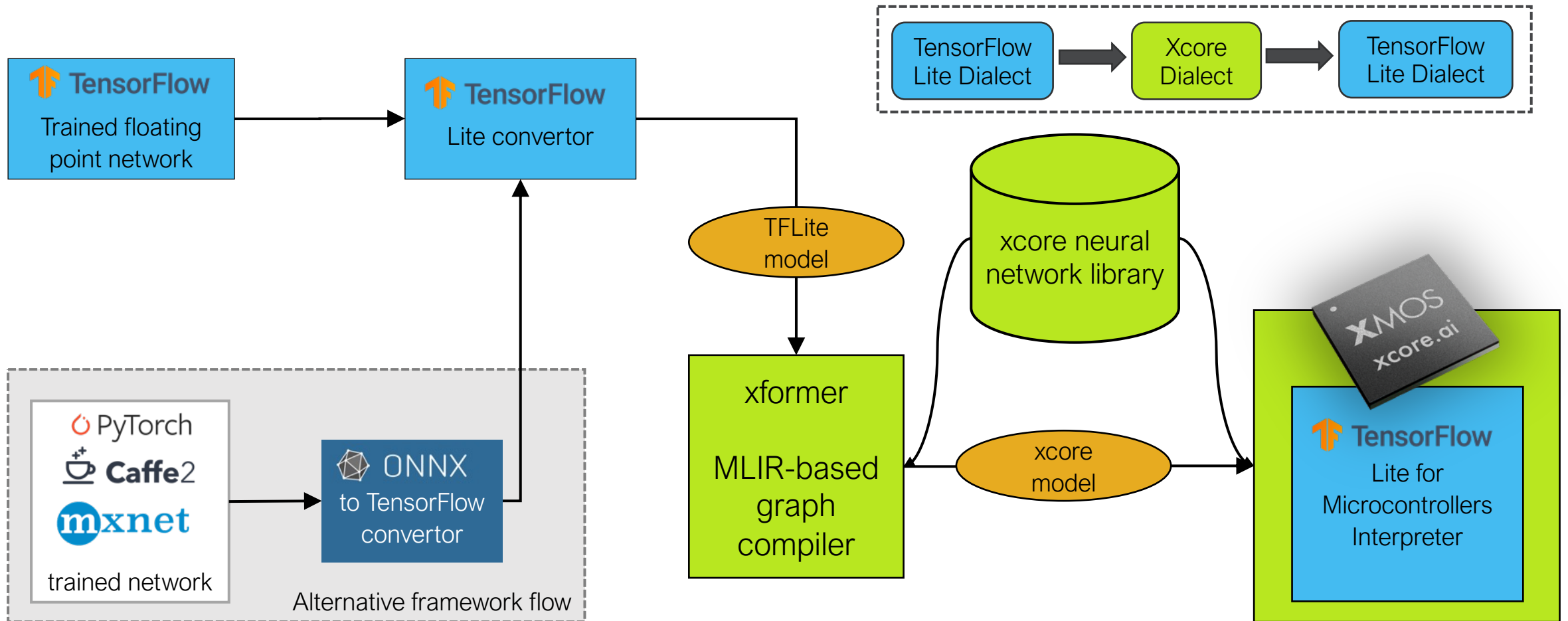


We have developed an MLIR-based graph compiler(xformer) to optimise TFLite models to deploy on xcore.ai



I will outline our workflow and focus on three MLIR passes implemented as part of memory usage optimisations

OPTIMISED WORKFLOW WITH GRAPH COMPILER



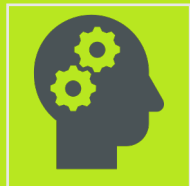
INTERPRETER-LESS WORKFLOW



Why interpreter-less?

Code size is critical - only include the code for operators used in the model

Remove unnecessary runtime overhead such as interpreter setup and such code



tflite-micro-compiler

A tiny open-source project

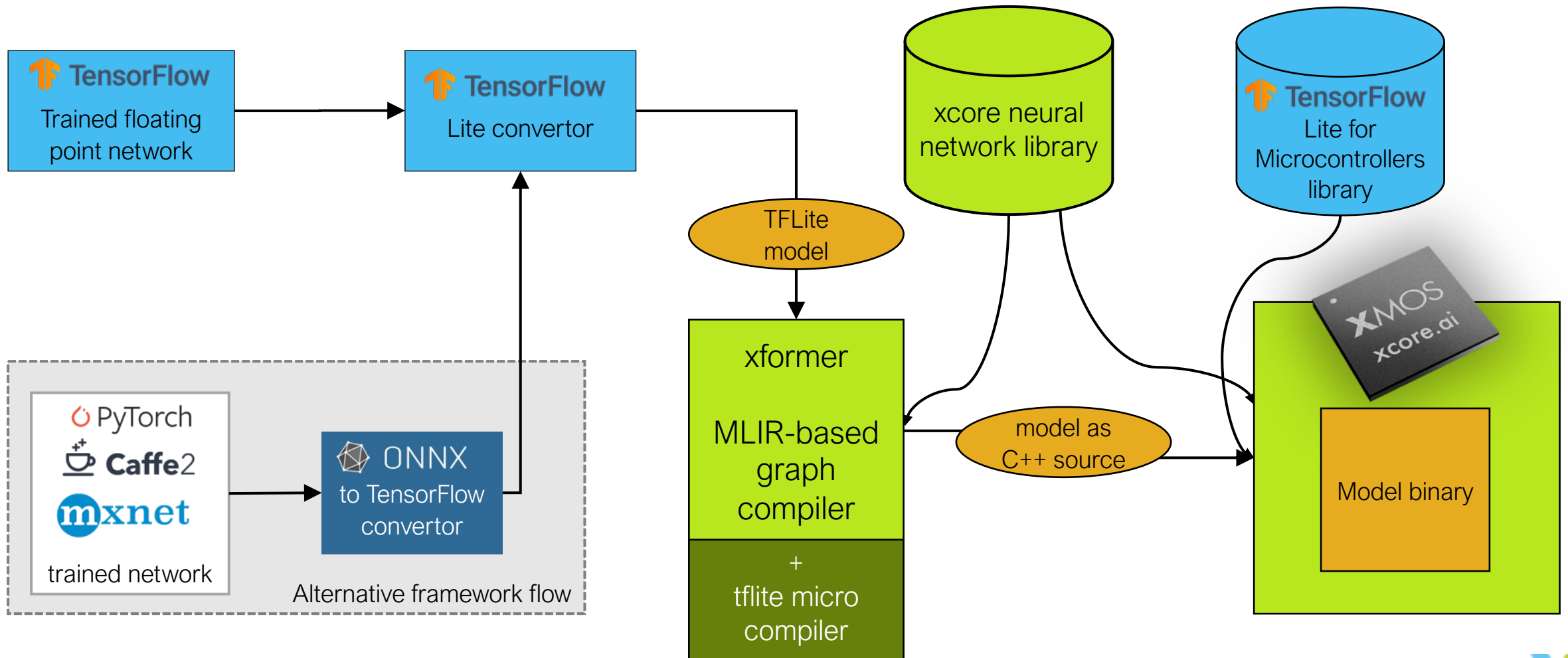
Runs tflite-micro interpreter and logs runtime info

Generates a C++ file for the model

https://github.com/cpetig/tflite_micro_compiler



INTERPRETER-LESS WORKFLOW



AN EXAMPLE – MOBILENETV2 (160X160X3, ALPHA = 1.0)

	Unoptimised	Initial optimisations	Arena planning	Operation splitting	Offloading to flash
RAM used (KB)	1385				
Binary size (KB)	2590				



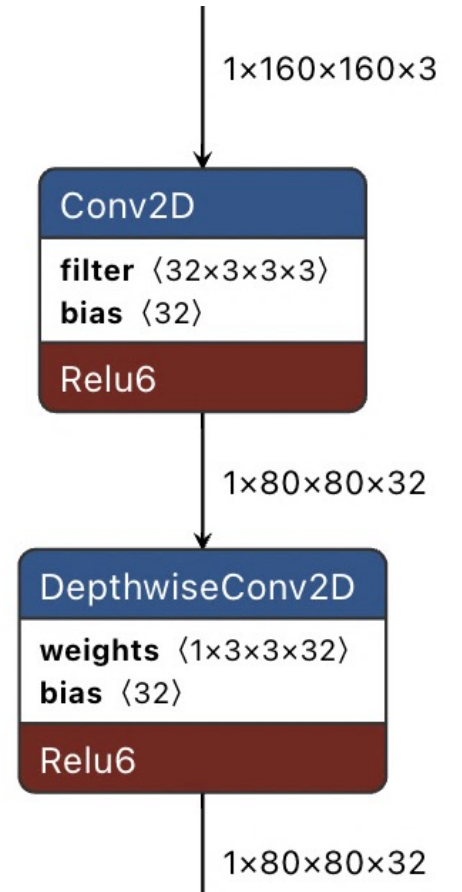
AN EXAMPLE – MOBILENETV2 (160X160X3, ALPHA = 1.0)

	Unoptimised	Initial optimisations	Arena planning	Operation splitting	Offloading to flash
RAM used (KB)	1385	1258			
Binary size (KB)	2590	2312			



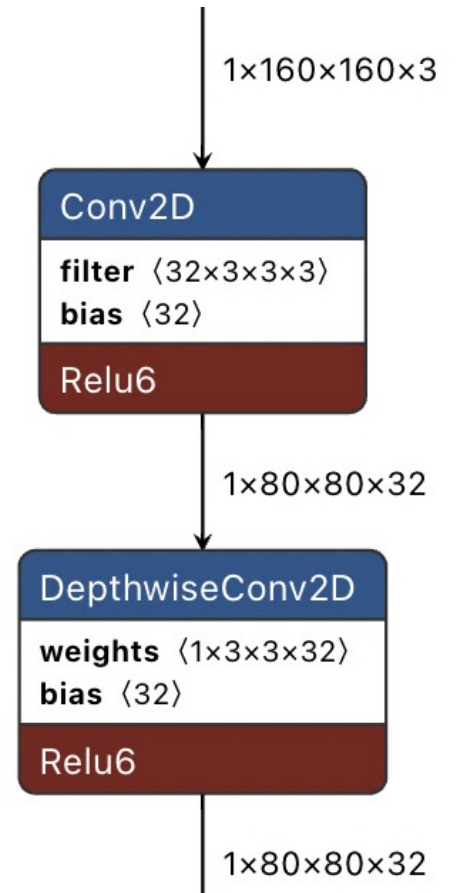
MEMORY PLAN ANALYSIS PASS

- Plans the tensor arena and allocates offsets for tensors



MEMORY PLAN ANALYSIS PASS

- `%2 = "tfl.conv_2d"(%arg0, %0, %1) {dilation_h_factor = 1 : i32, dilation_w_factor = 1 : i32, fused_activation_function = "RELU6", padding = "SAME", stride_h = 2 : i32, stride_w = 2 : i32} :`
(tensor<?x160x160x3x!quant.uniform<i8:f32, 0.0039215688593685627:-128>>, tensor<32x3x3x3x!quant.uniform<i8<-127:127>:f32:0, 0.0052513480186462402>>, tensor<32x!quant.uniform<i32:f32:0, 2.0593523004208691E-5>>) -> tensor<?x80x80x32x!quant.uniform<i8:f32, 0.023529412224888802:-128>>
- `%5 = "tfl.depthwise_conv_2d"(%2, %3, %4) {depth_multiplier = 1 : i32, dilation_h_factor = 1 : i32, dilation_w_factor = 1 : i32, fused_activation_function = "RELU6", padding = "SAME", stride_h = 1 : i32, stride_w = 1 : i32} :` (tensor<?x80x80x32x!quant.uniform<i8:f32, 0.023529412224888802:-128>>, tensor<1x3x3x32x!quant.uniform<i8<-127:127>:f32:3, 0.021009480580687523}>>, tensor<32x!quant.uniform<i32:f32:0, 4.9434072570875287E-4>>) -> tensor<?x80x80x32x!quant.uniform<i8:f32, 0.023529412224888802:-128>>



MEMORY PLAN ANALYSIS PASS

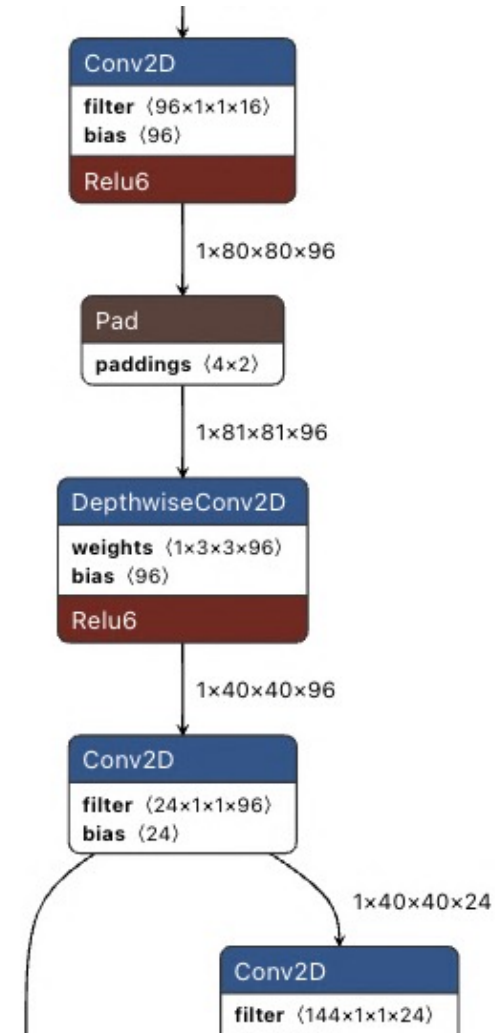
Walk and calculate non-constant tensor sizes

Prepare map of firstUsed and lastUsed ops

Identify ops that can be overlapped

Greedy allocate offsets for size-sorted tensors

Prepare the allocation plan



MEMORY PLAN ANALYSIS PASS

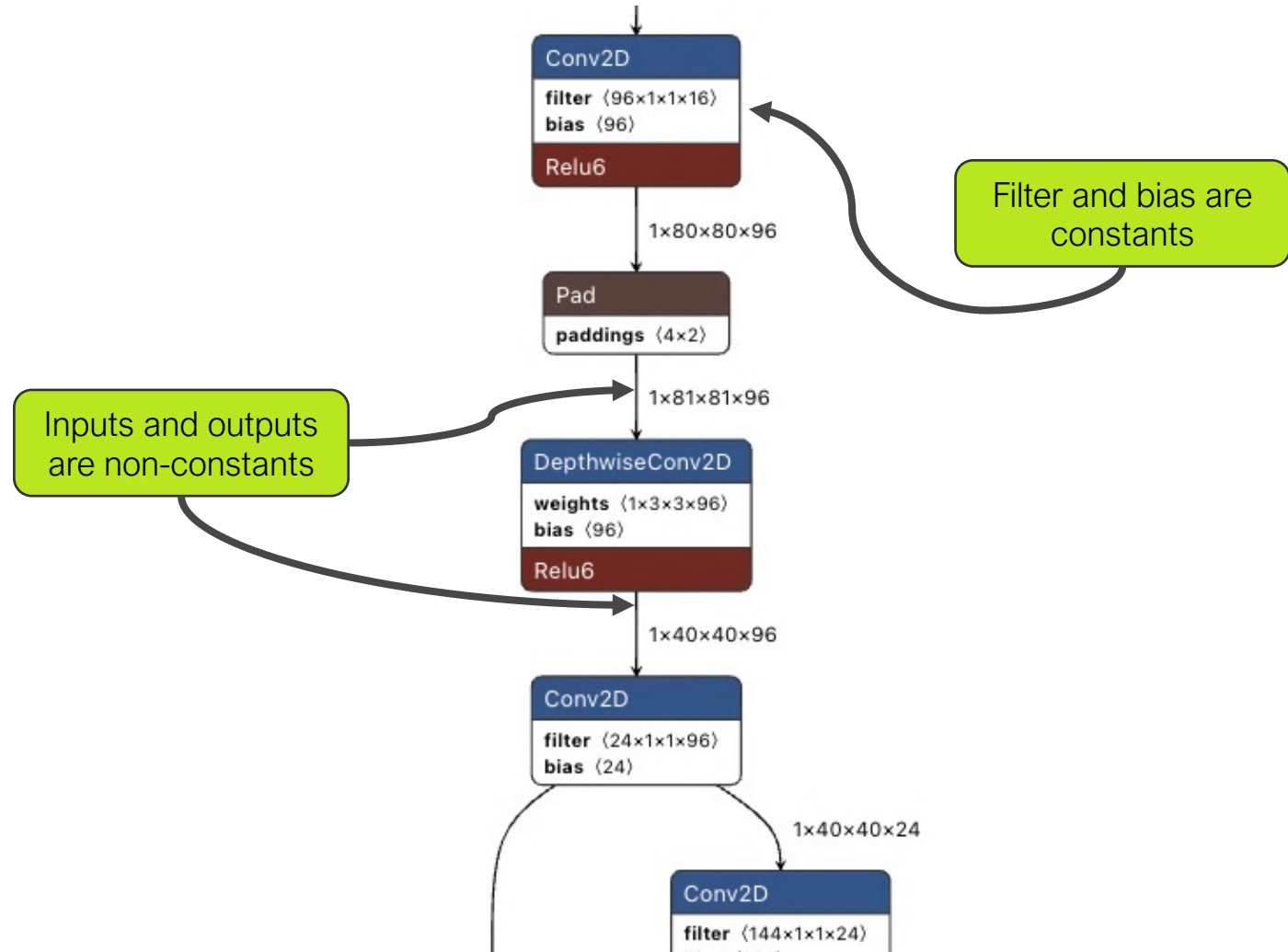
Walk and calculate non-constant tensor sizes

Prepare map of firstUsed and lastUsed ops

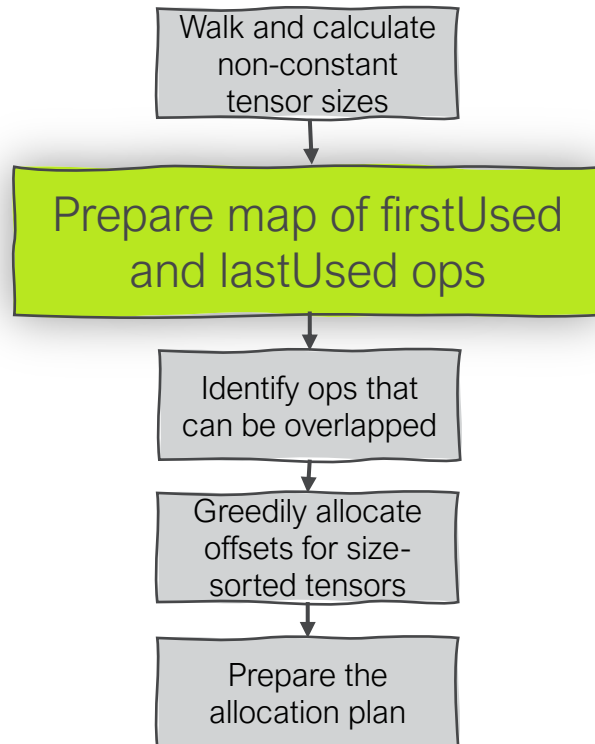
Identify ops that can be overlapped

Greedy allocate offsets for size-sorted tensors

Prepare the allocation plan



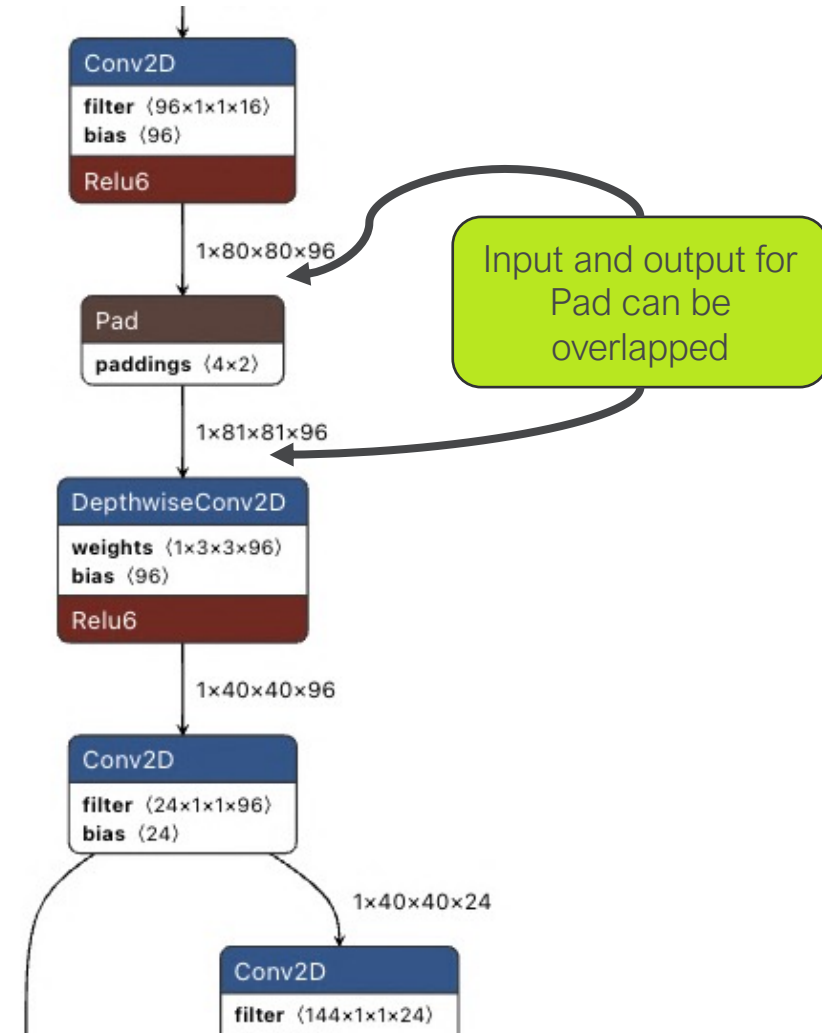
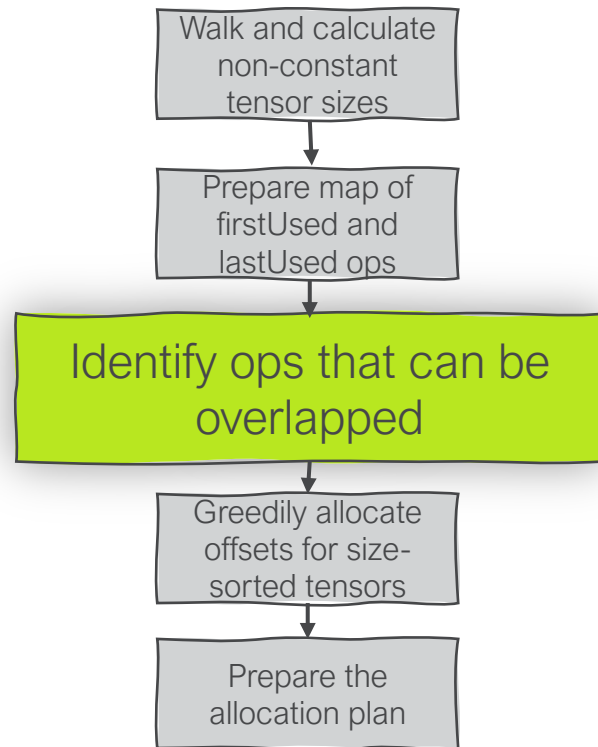
MEMORY PLAN ANALYSIS PASS



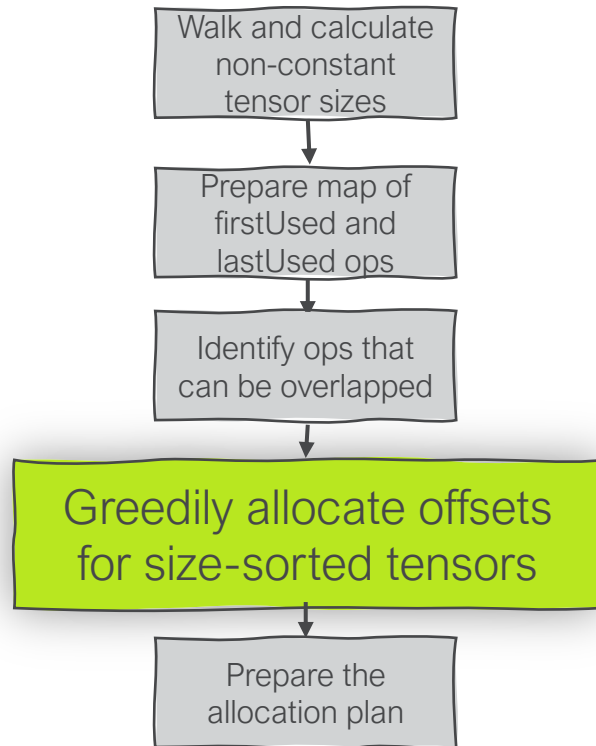
- Use Liveness Analysis pass in MLIR
- This is used to identify simultaneously alive tensors
- The largest simultaneously alive tensors defines the peak memory usage for the graph



MEMORY PLAN ANALYSIS PASS



MEMORY PLAN ANALYSIS PASS



- The allocation algorithm is similar to the one used in Tensorflow Lite for Microcontrollers for arena planning
- Doing it in MLIR gives us much more control
- We want to minimise the total memory used while avoiding fragmentation



AN EXAMPLE – MOBILENETV2 (160X160X3, ALPHA = 1.0)

	Unoptimised	Initial optimisations	Arena planning	Operation splitting	Offloading to flash
RAM used (KB)	1385	1258			
Binary size (KB)	2590	2312			



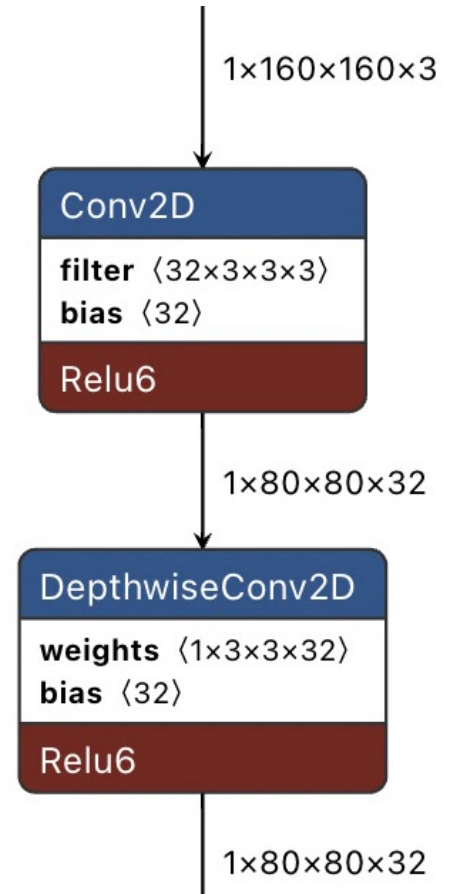
AN EXAMPLE – MOBILENETV2 (160X160X3, ALPHA = 1.0)

	Unoptimised	Initial optimisations	Arena planning	Operation splitting	Offloading to flash
RAM used (KB)	1385	1258	798		
Binary size (KB)	2590	2312	2312		

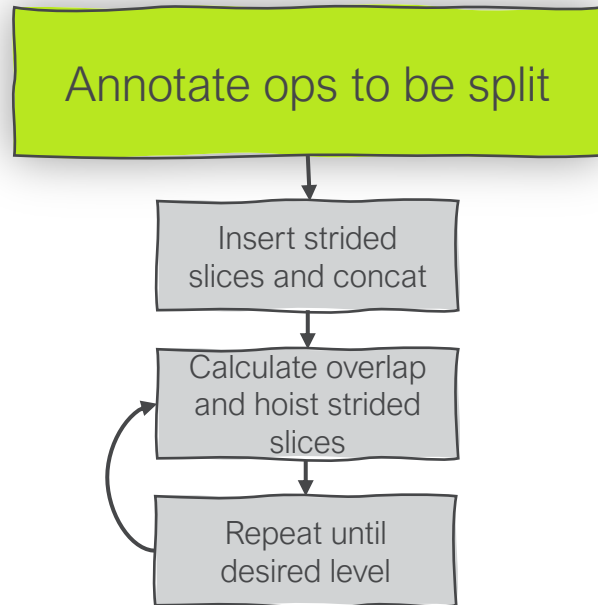


OPERATION SPLIT PASS

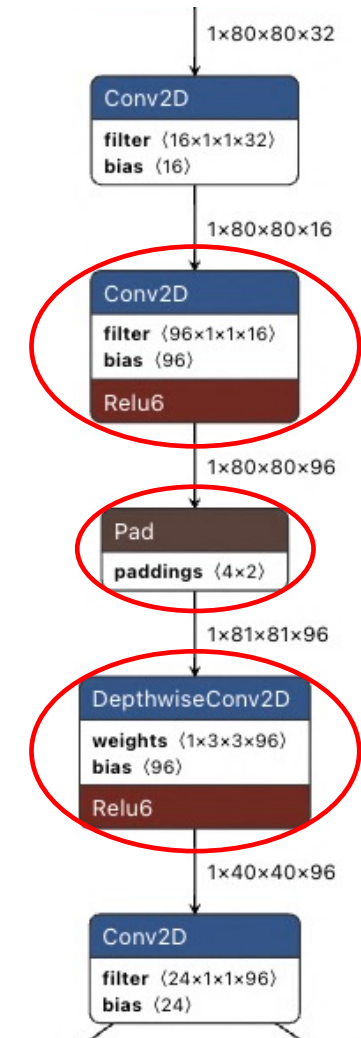
- Splits operations into multiple ops to reduce peak memory usage



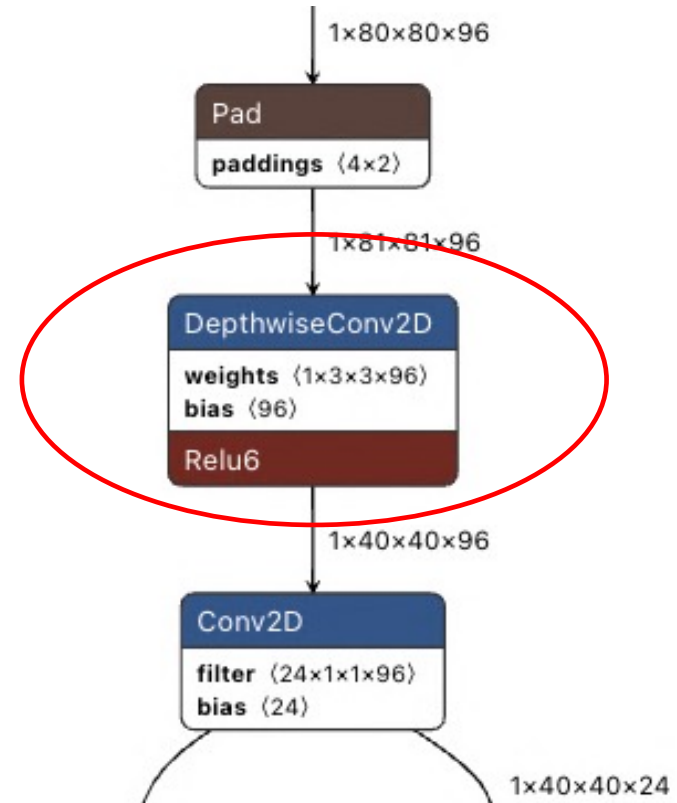
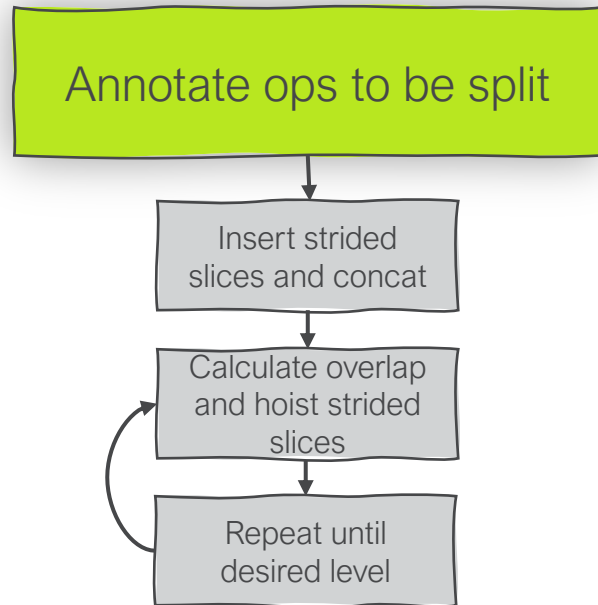
OPERATION SPLIT PASS



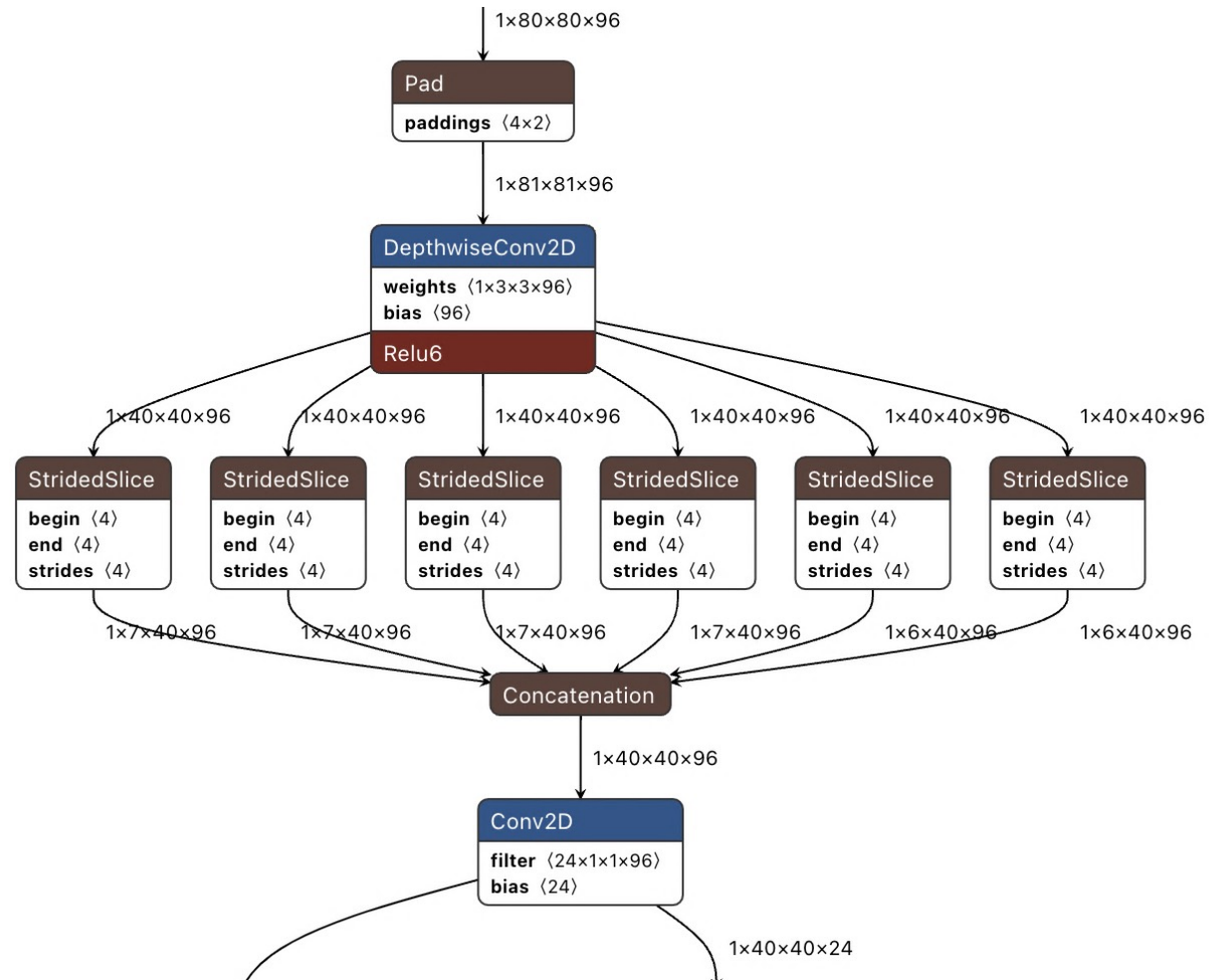
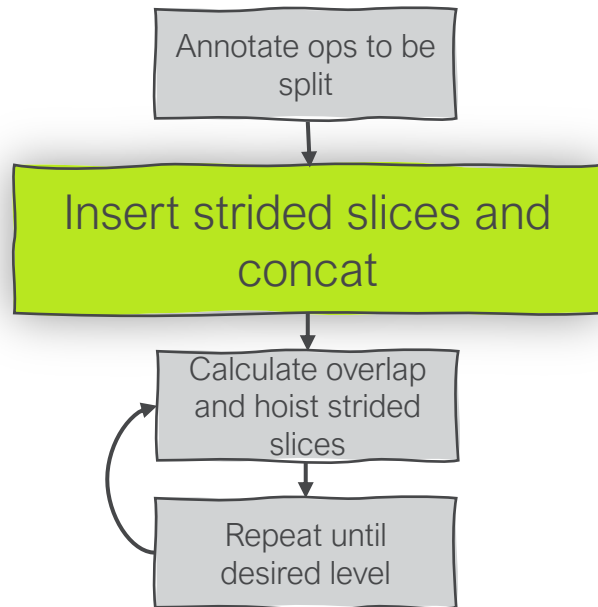
- Annotation can be specified by command-line options
- We also have partially working auto-annotation based on Liveness Analysis pass and peak memory usage



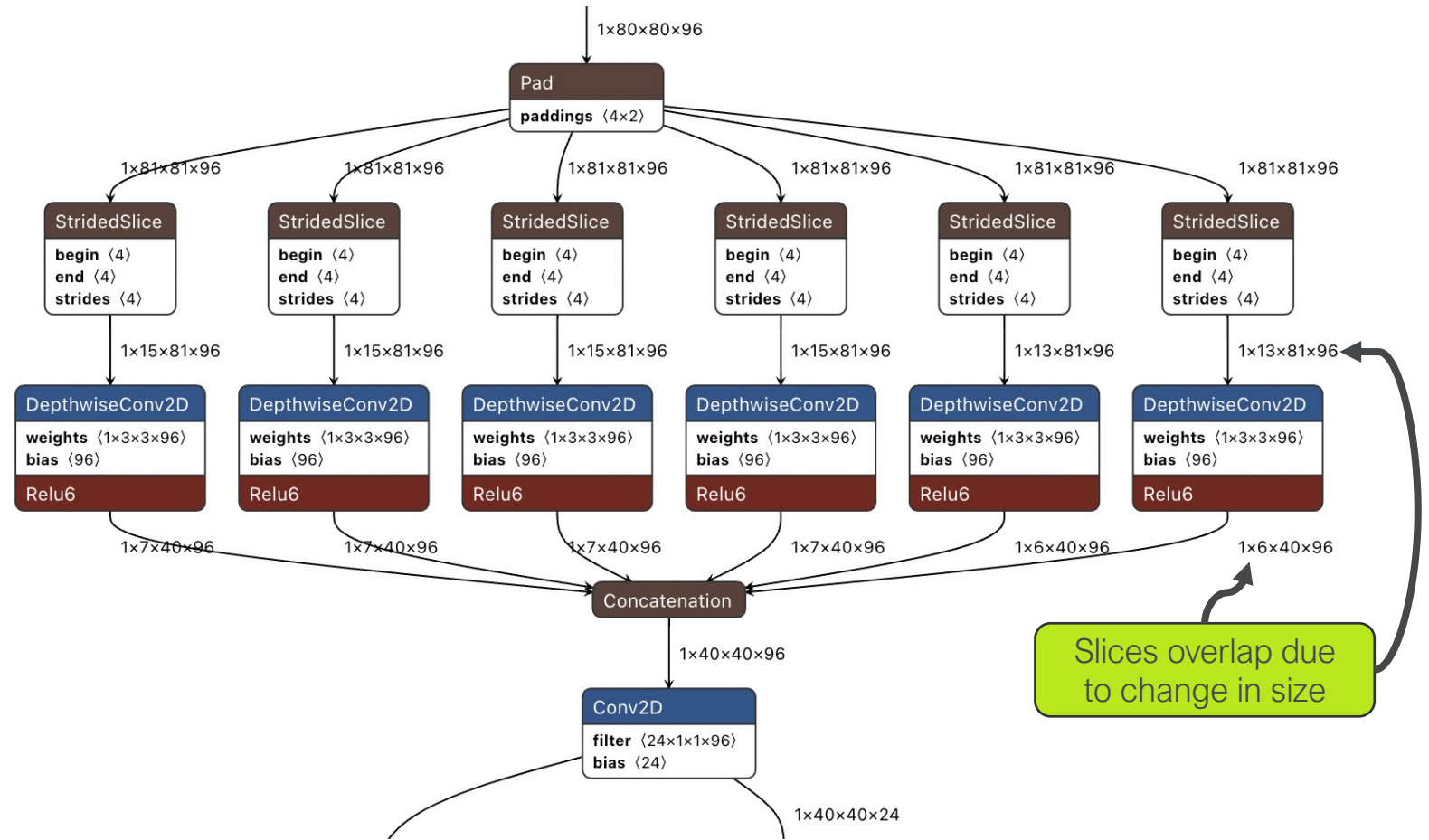
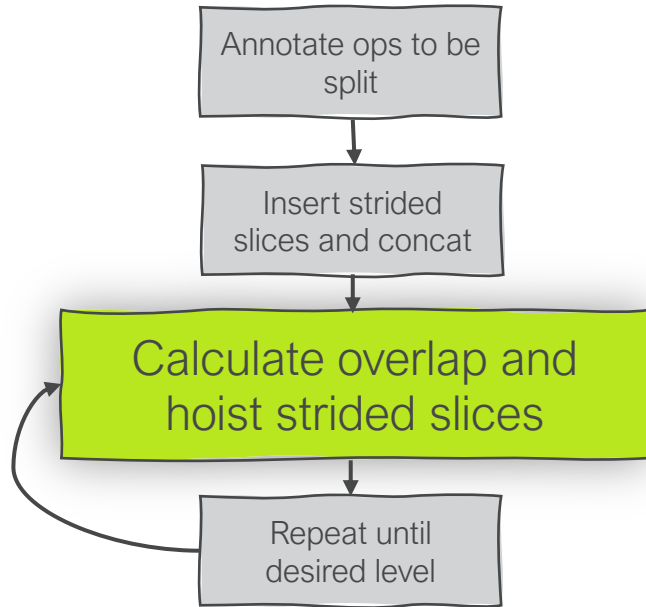
OPERATION SPLIT PASS



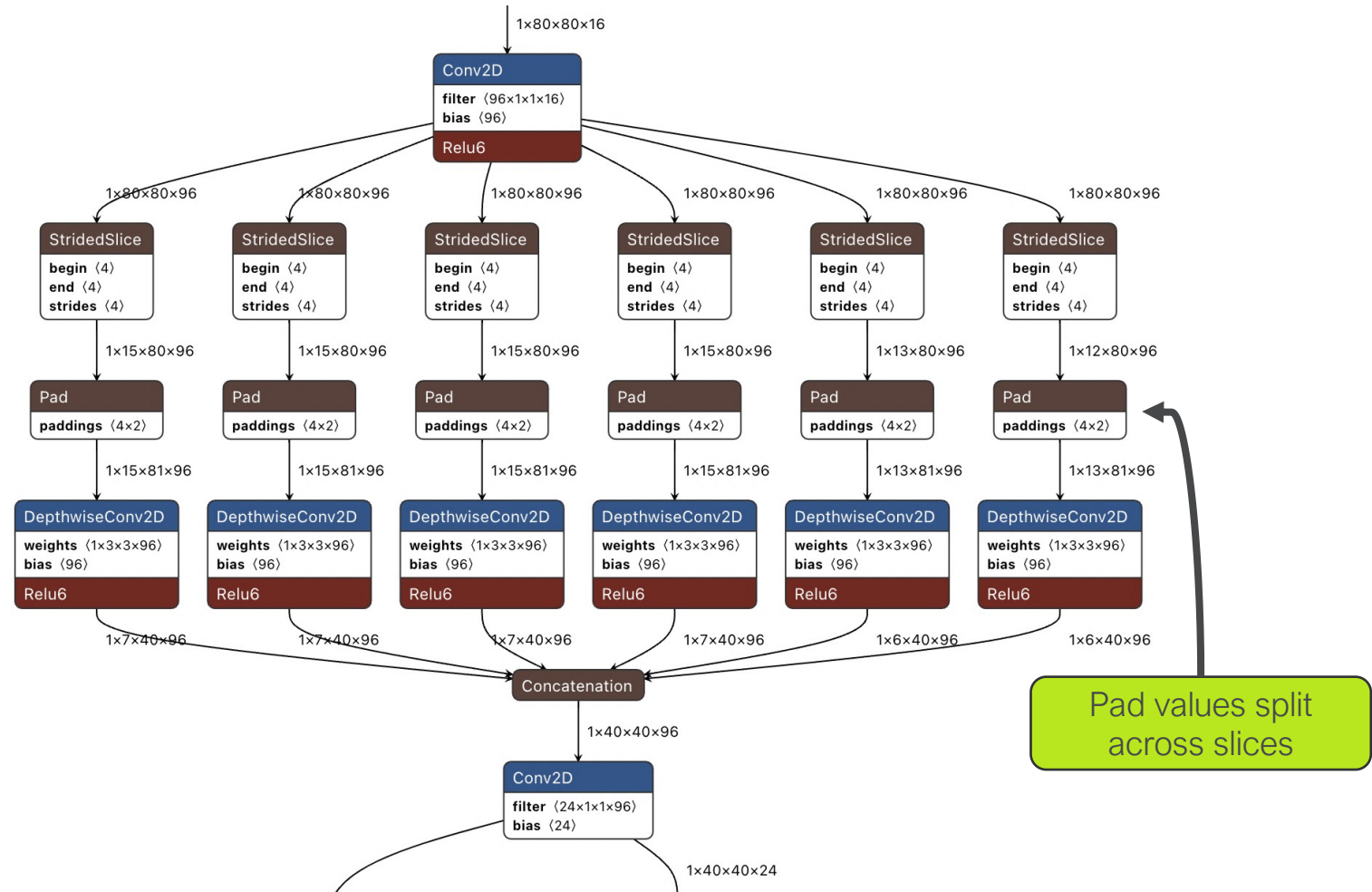
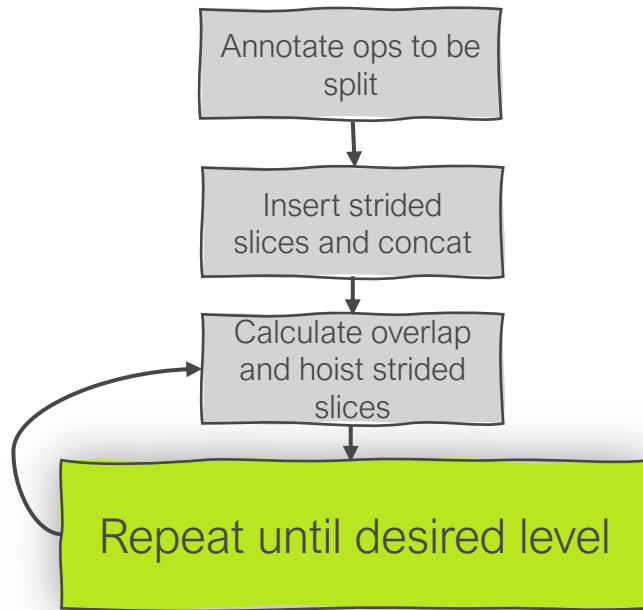
OPERATION SPLIT PASS



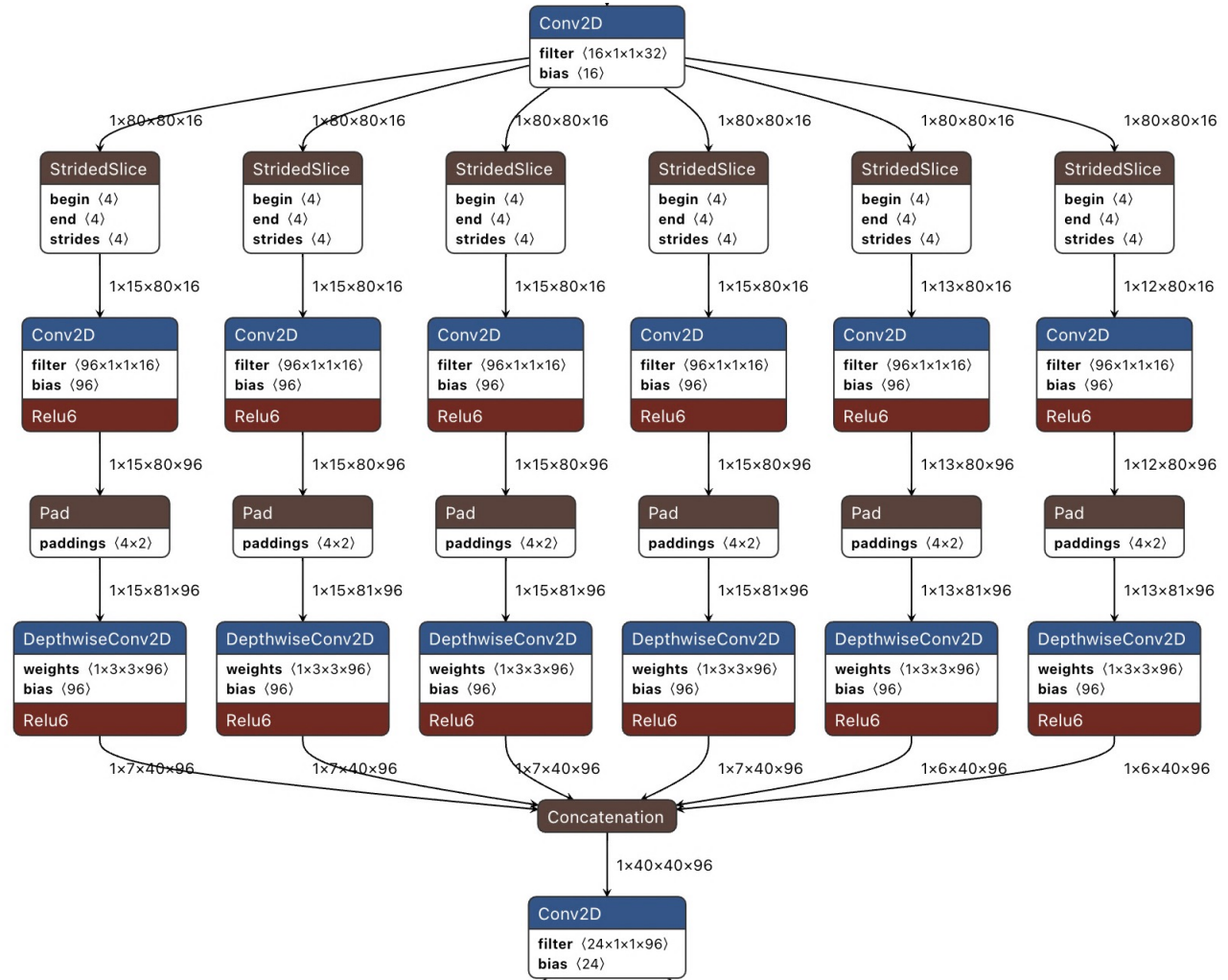
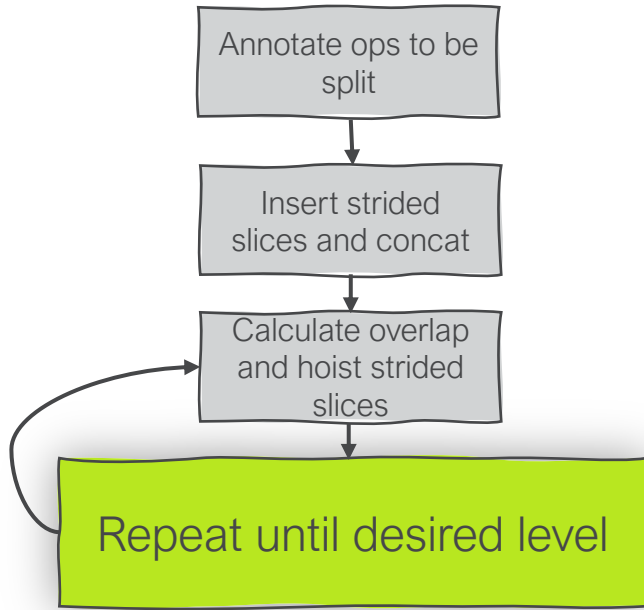
OPERATION SPLIT PASS



OPERATION SPLIT PASS



OPERATION SPLIT PASS



AN EXAMPLE – MOBILENETV2 (160X160X3, ALPHA = 1.0)

	Unoptimised	Initial optimisations	Arena planning	Operation splitting	Offloading to flash
RAM used (KB)	1385	1258	798		
Binary size (KB)	2590	2312	2312		



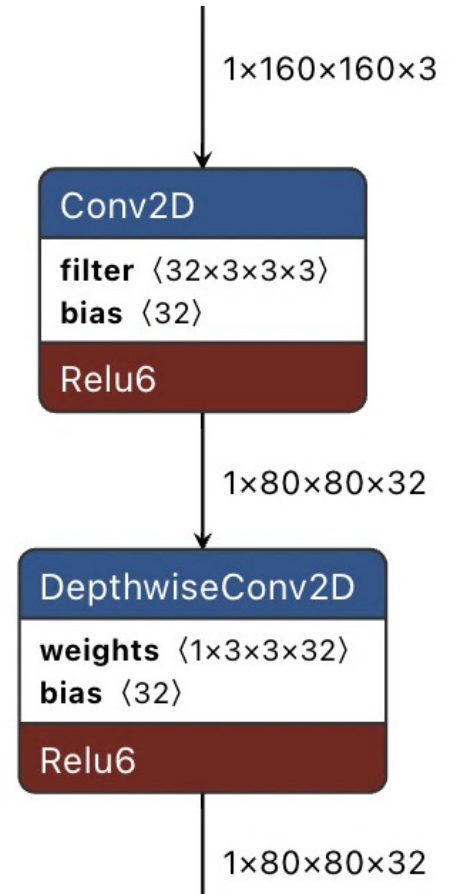
AN EXAMPLE – MOBILENETV2 (160X160X3, ALPHA = 1.0)

	Unoptimised	Initial optimisations	Arena planning	Operation splitting	Offloading to flash
RAM used (KB)	1385	1258	798	363	
Binary size (KB)	2590	2312	2312	2337	



FLASH IMAGE PASS

- Offload weights in the model to a flash image which can then be streamed in at runtime

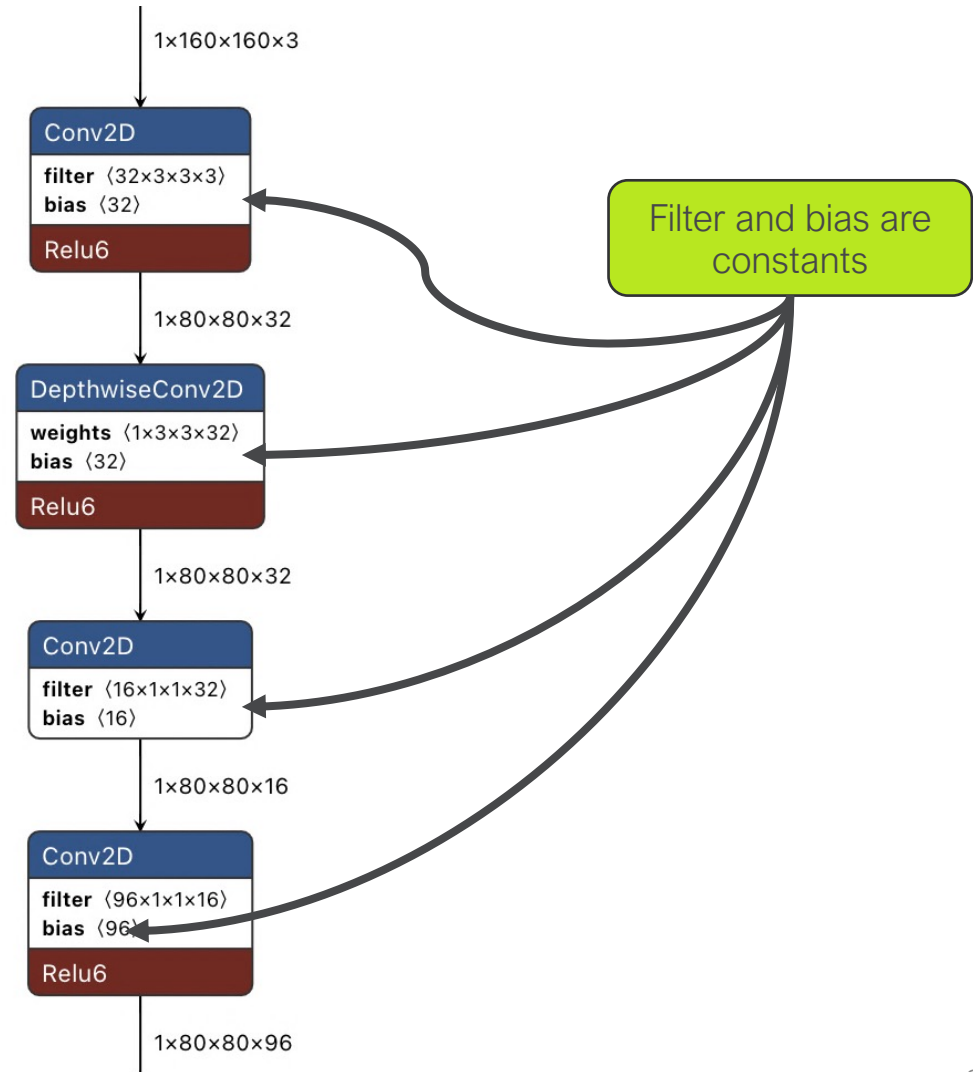


FLASH IMAGE PASS

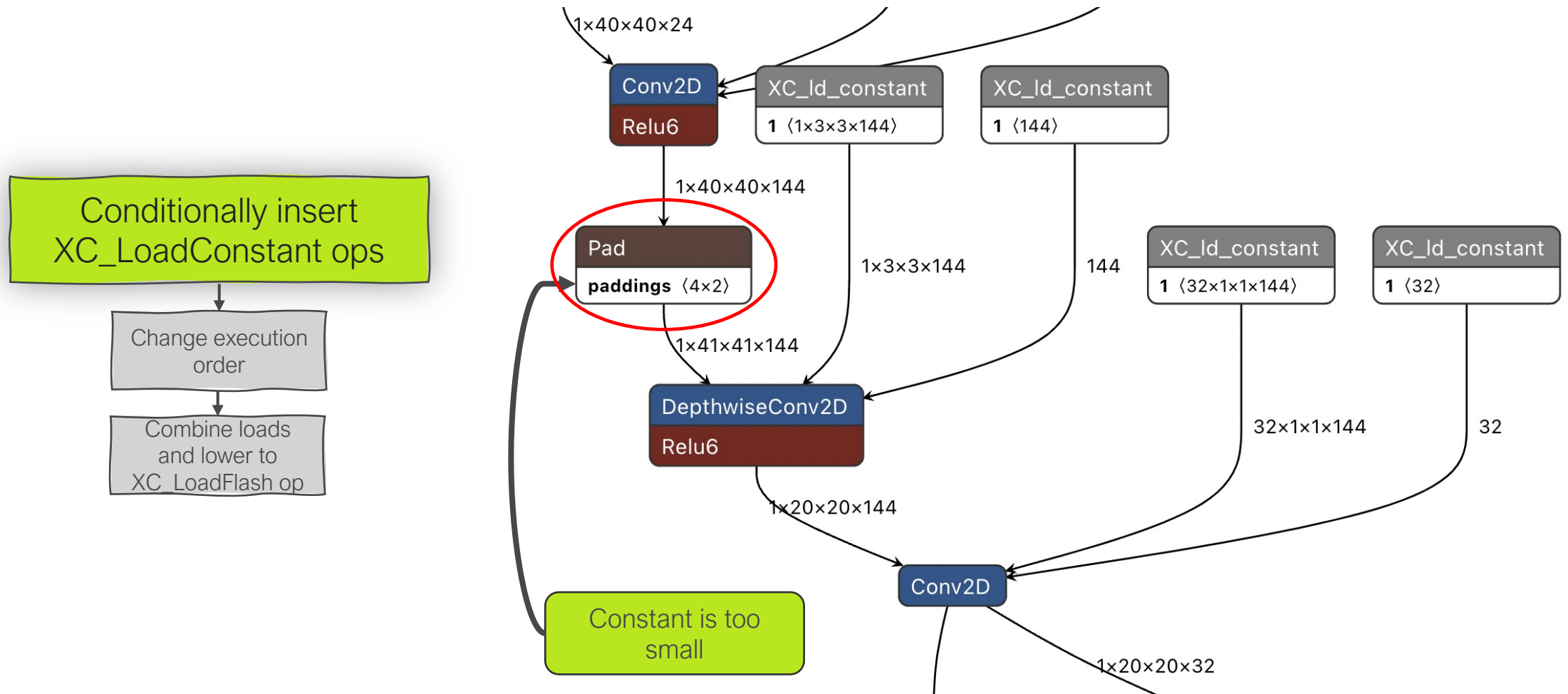
Conditionally insert
XC_LoadConstant ops

Change execution
order

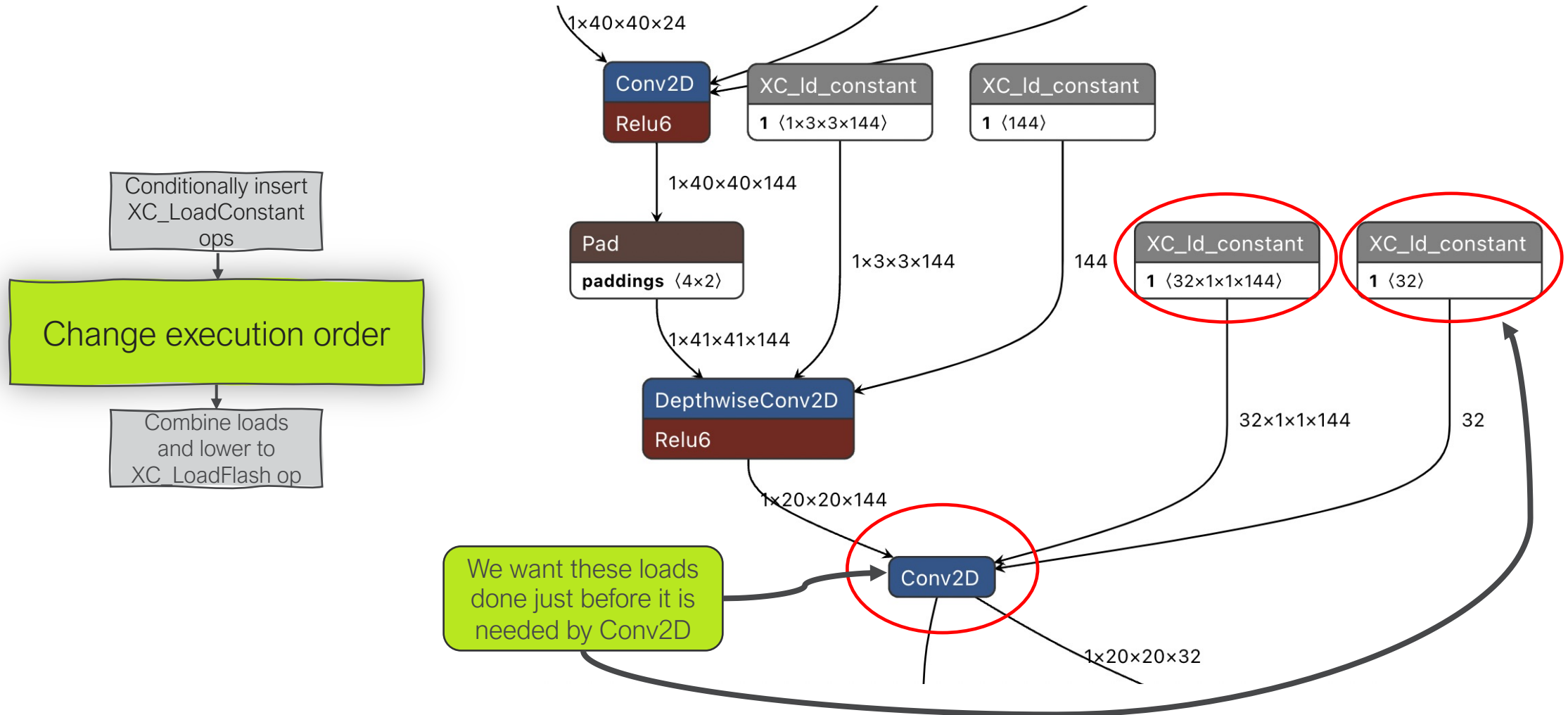
Combine loads
and lower to
XC_LoadFlash op



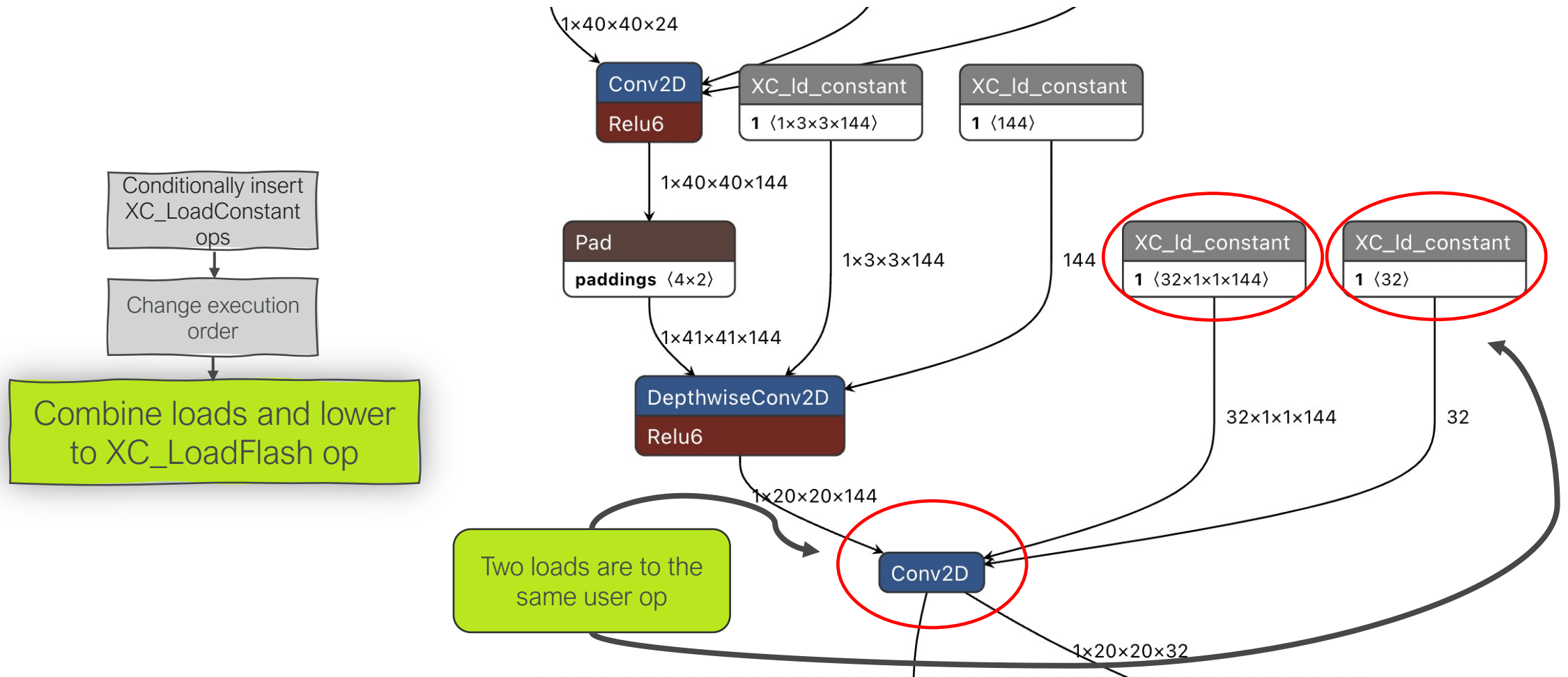
FLASH IMAGE PASS



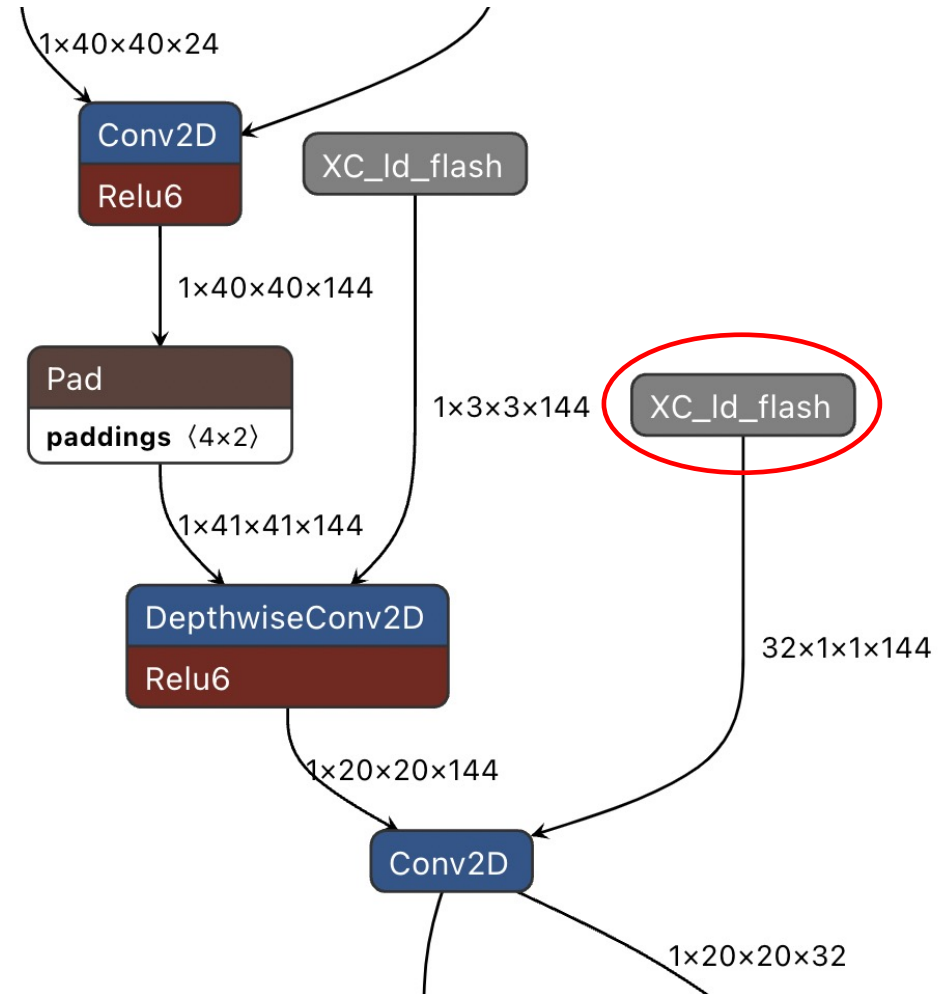
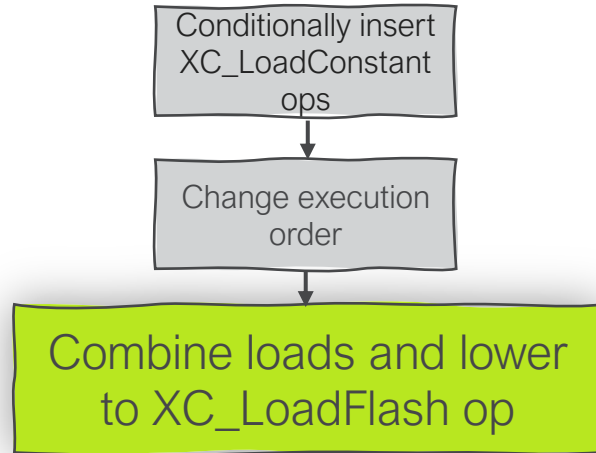
FLASH IMAGE PASS



FLASH IMAGE PASS



FLASH IMAGE PASS



AN EXAMPLE – MOBILENETV2 (160X160X3, ALPHA = 1.0)

	Unoptimised	Initial optimisations	Arena planning	Operation splitting	Offloading to flash
RAM used (KB)	1385	1258	798	363	
Binary size (KB)	2590	2312	2312	2337	

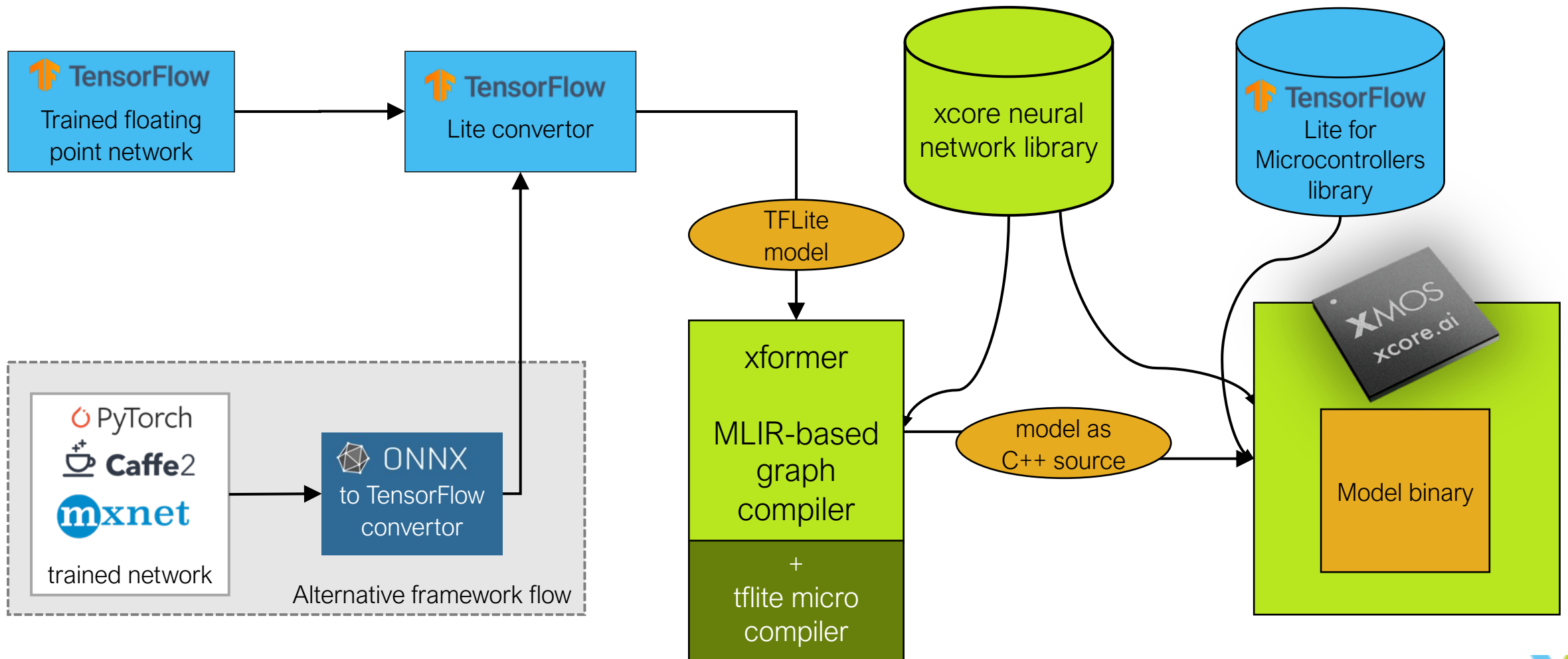


AN EXAMPLE – MOBILENETV2 (160X160X3, ALPHA = 1.0)

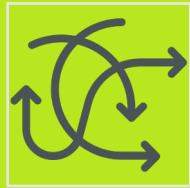
	Unoptimised	Initial optimisations	Arena planning	Operation splitting	Offloading to flash
RAM used (KB)	1385	1258	798	363	384
Binary size (KB)	2590	2312	2312	2337	488



CHALLENGES AND FUTURE PLANS



CHALLENGES AND FUTURE PLANS



Challenges

Identify prior art to reuse

Find what is the “correct” way, what idioms to use



Future plans

Adapt memory plan analysis to add page in/out ops for handling larger models

Better execution order

EXPERIENCE WITH MLIR



The MLIR framework made it easy for us to quickly add optimisations and productise our AI tools



We reuse a lot of code from TensorFlow and the MLIR project



Being able to work at the right level of abstraction is intuitive



- Thank you!
- deepakpanickal@xmos.com
- All code is available publicly at
- https://github.com/xmos/ai_tools
- https://github.com/xmos/lib_tflite_micro