

Machine learning with NIR

Tomeu Vizoso – tomeu@tomeuvizoso.net

Philipp Zabel – p.zabel@pengutronix.de



Agenda Part 1

- Difference between shader and NN operation graph
- ffma and conv2d
- Tensor operation replacements in etnaviv
 - Fusing non-linear activation functions
 - int8_t on uint8_t hardware
 - Addition using conv2d
 - Strided conv2d
 - Per-axis quantization



Shader vs neural network 1/2

- Shader
 - Basic unit: 32-bit float scalar
 - Arithmetic operations, load&store, flow control
 - Representative operation: fused multiplication and addition

Neural network

- Basic unit: tensor, quantization
- Convolutions, non-linear activation, element-wise arithmetic
- Saturated arithmetic
- Representative op: Conv2D



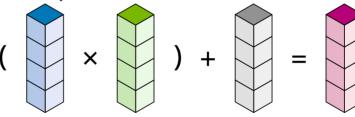
Shader vs neural network 2/2

Shader

- Basic unit: 32-bit float scalar or 4-vector
- Arithmetic operations, load&store, flow control
- Representative operation: fused multiplication and addition

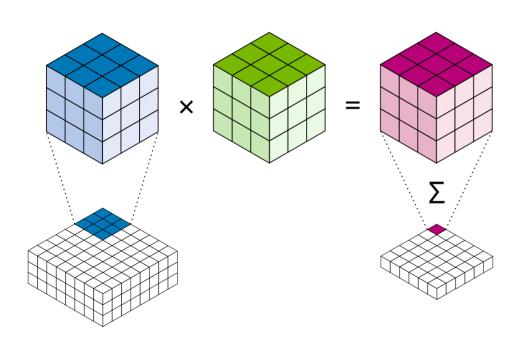
Neural network

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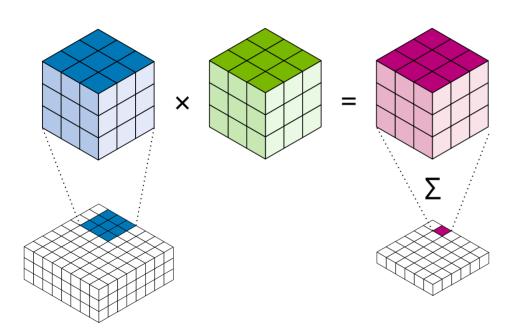


Conv2D_{1/6}



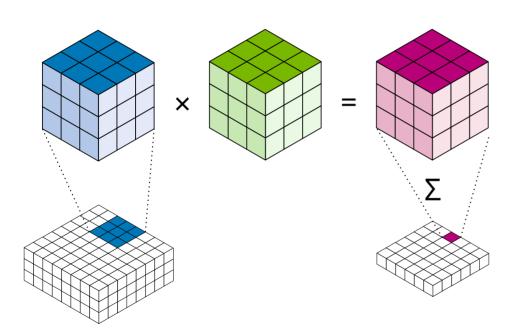
- Tensor input
- 8-bit quantization [1] r = S * (q z)
- Weight tensor constant, compressed
- w_x*w_y*w_z muls, Σ together around each 2D input pos

Conv2D_{2/6}



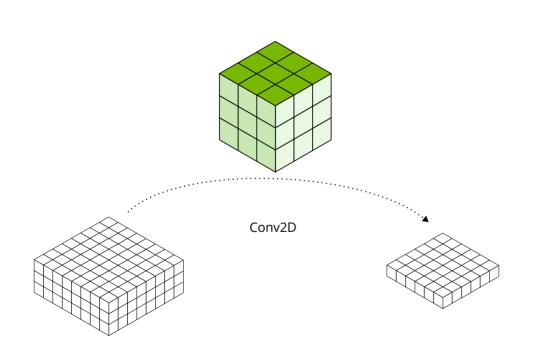
- Tensor input
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Conv2D 3/6



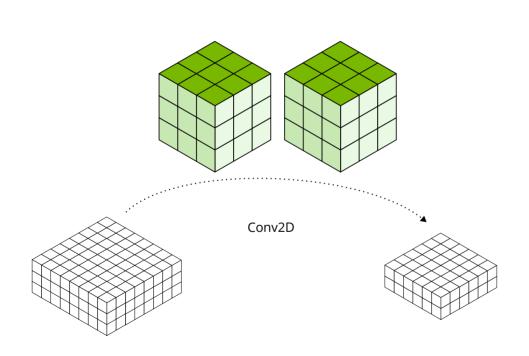
- Tensor input
- 8-bit quantization [1] r = S * (q z)
- Weight tensor constant, compressed
- w_x*w_y*w_z muls, Σ together around each 2D input pos

Conv2D 4/6



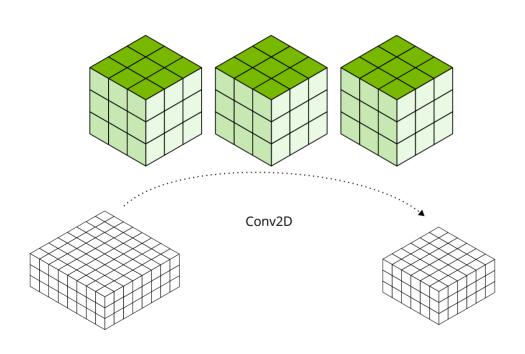
 4th weight dimension for multiple output channels

Conv2D 5/6



- 4th weight dimension for multiple output channels
- allows work to be split over multiple cores

Conv2D 6/6

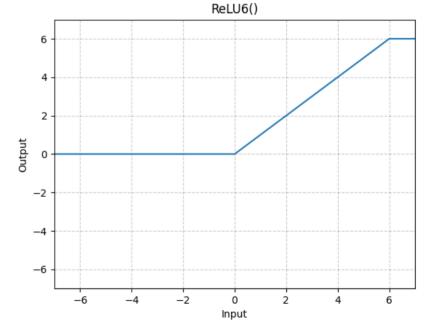


- 4th weight dimension for multiple output channels
- allows work to be split over multiple cores



Fusing activation

- Some non-linear activation functions can be fused into preceding operations
- Hardware supports fused convolution + ReLU
- ReLU6 is a no-op if output tensor quantization limits are within [0...6]



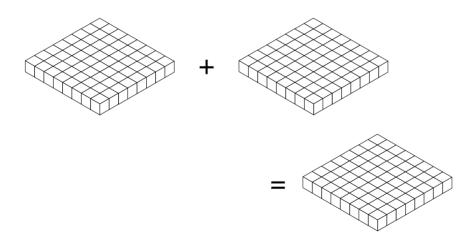


int8_t on uint8_t-only hardware

- Model specifies int8_t quantization
- Hardware only supports uint8_t
- Add 128 to all inputs, to move from [-128..127] to [0..255],
 subtract 128 from all output tensors
- Adapt tensor zero points and do all operations on uint8_t tensors



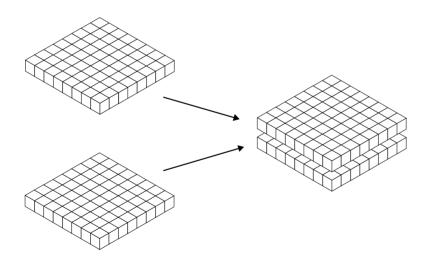
Addition using conv2d _{1/3}



- No fixed function tensortensor addition
- Shader fallback slow



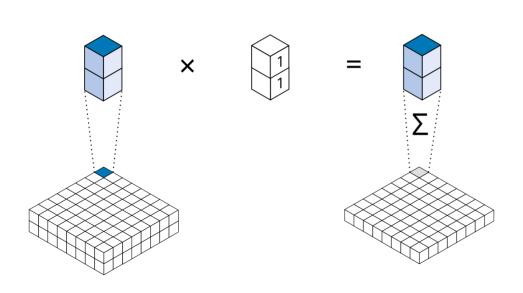
Addition using conv2d _{2/3}



- No fixed function tensortensor addition
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- Concatenate input tensors



Addition using conv2d 3/3

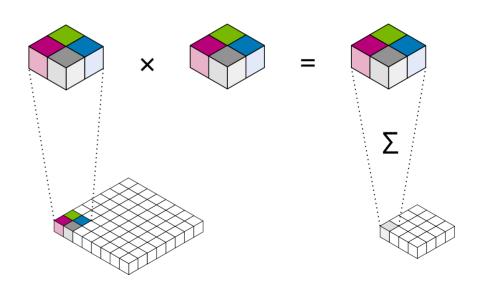


- No fixed function tensortensor addition
- Shader fallback slow
- Concatenate input tensors
- Use conv2d with 2 channels and kernel containing 1.0s



Strided conv2d 1/6

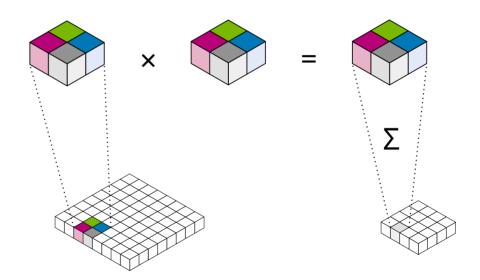
- e.g. stride = 2
- No hardware support





Strided conv2d 2/6

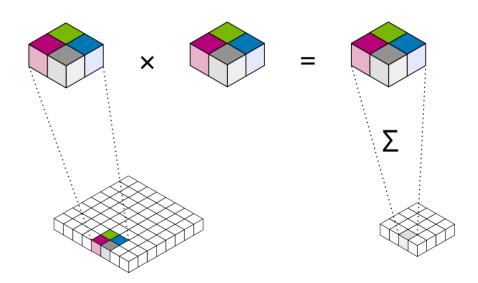
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Strided conv2d 3/6

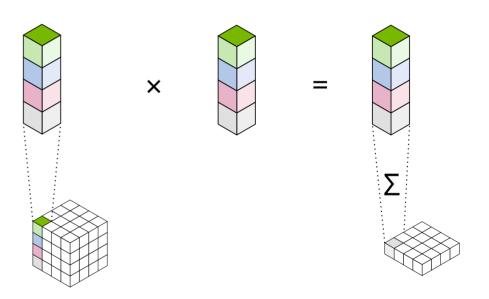
- e.g. stride = 2
- No hardware support





Strided conv2d 4/6

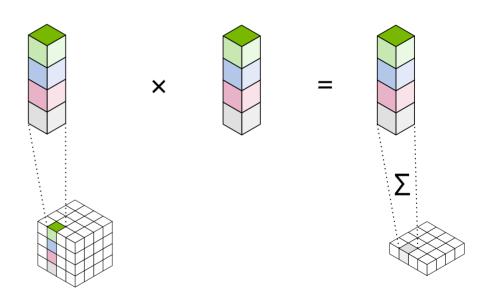
- e.g. stride = 2
- No hardware support
- Reorder input and weight tensor [1]





Strided conv2d 5/6

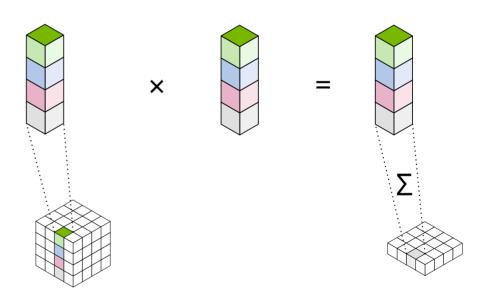
- e.g. stride = 2
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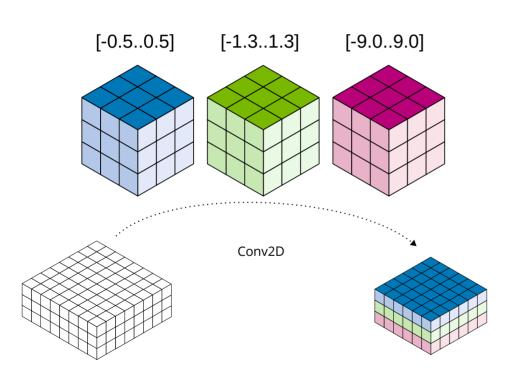
Strided conv2d 6/6

- e.g. stride = 2
- No hardware support
- Reorder input and weight tensor [1]





Per-axis quantization



- Weight tensor quantization per output channel [1]
- Split into multiple conv2d with a single output channel each
- Concatenate output tensors
- Overhead scales with number of channels
- Reduces parallelism in etnaviv



Current situation: Gallium

```
struct pipe_tensor {
   struct pipe_resource *resource;
   unsigned index;
   unsigned dims[4];
   float scale;
   float *scales;
   int zero_point;
   int *zero_points;
   bool is_signed;
};
```



Current situation: Gallium (2)

```
enum pipe_ml_operation_type {
   PIPE ML OPERATION TYPE ADD,
   PIPE ML OPERATION TYPE CONVOLUTION,
   PIPE ML OPERATION TYPE POOLING,
   PIPE ML OPERATION TYPE CONCATENATION,
   PIPE ML OPERATION TYPE SPLIT,
   PIPE ML OPERATION TYPE PAD,
   PIPE ML OPERATION TYPE FULLY CONNECTED,
   PIPE ML OPERATION TYPE RESHAPE,
   PIPE ML OPERATION TYPE RELU,
   PIPE ML OPERATION TYPE ABSOLUTE,
   PIPE ML OPERATION TYPE LOGISTIC,
   PIPE_ML_OPERATION_TYPE_SUBTRACT,
   PIPE ML OPERATION TYPE TRANSPOSE,
```



Current situation: Gallium (3)

```
struct pipe_ml_operation
   enum pipe_ml_operation_type type;
   struct pipe_tensor **input_tensors;
   unsigned input_count;
   struct pipe_tensor **output_tensors;
   unsigned output_count;
   union {
      struct {
         struct pipe_tensor *weight_tensor;
         struct pipe_tensor *bias_tensor;
         unsigned stride_x;
         unsigned stride_y;
```

```
bool padding same;
  bool pointwise;
  bool depthwise;
  bool relu;
  unsigned dilation_width_factor;
  unsigned dilation height factor;
 conv;
struct {
  unsigned stride x;
  unsigned stride_y;
  unsigned filter_width;
  unsigned filter_height;
  bool padding_same;
 pooling;
```

Current situation: Drivers

```
#define MAX TENSORS 10
struct etna_operation {
   struct list_head link;
   enum etna_job_type type;
   enum etna_ml_tp_type tp_type;
   bool addition;
   bool depthwise;
   bool pointwise;
   bool fully connected.
   bool bool etna_operation::padding_same
   bool padding_same;
   bool relu;
   unsigned stride;
```

```
unsigned input_tensors[MAX_TENSORS];
unsigned input count;
unsigned input_tensor_sizes[MAX_TENSORS];
unsigned input width;
unsigned input_height;
unsigned input_channels;
uint8 t input zero point;
float input_scale;
unsigned output_tensors[MAX_TENSORS];
unsigned output_count;
unsigned output_tensor_sizes[MAX_TENSORS];
```

Current situation: Drivers (2)

```
struct etna_vip_instruction {
   enum etna_job_type type;
   enum etna_ml_tp_type tp_type;
   struct etna_bo *configs[MAX_CONFIG_BOS];
   struct etna_bo *coefficients;
   struct etna_bo *pwl_lut;
   struct pipe_resource *input;
   unsigned input offset;
   struct pipe_resource *output;
   unsigned output_offset;
   struct etna_bo *kernel;
```



Proposal: Use NIR as the base for these IRs

- RFC: Add tensor operations to NIR
- https://gitlab.freedesktop.org/mesa/mesa/-/merge_requests/35441/



Tensor GLSL type (src/compiler)

- New GLSL_TYPE_TENSOR in enum glsl_base_type
- New description for this type:

```
-#define GLSL_MAX_TENSOR_RANK 4
--
struct glsl_tensor_description {
    enum glsl_base_type element_type;
    uint8_t rank; // Number of dimensions (e.g., 2 for matrix, 4 for a 4D tensor)
    uint32_t dims[GLSL_MAX_TENSOR_RANK]; // Array of dimension sizes (e.g., {D0, D1, D2, D3})
    int zero_point;
    float scale;
    bool channels_last;
--};
```



How intrinsics use the tensor type

- Each tensor used in a graph is represented by a nir_variable with a glsl_base_type of GLSL_TYPE_TENSOR
- Intrinsics such as nir_conv2d operate on references to these variables
- The glsl_tensor_description struct contains all information that defines the type of the tensor. We can deref the nir_def, then get the tensor description (deref >type)



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Intrinsics

```
intrinsic(name='conv2d',
         src_comp=[-1, -1, -1, -1], # Srcs: InputTensorHandle, KernelTensorHandle,
         dest_comp=-1,  # No SSA destination; output is via writing to
         indices=[STRIDE_X, STRIDE_Y, PADDING, DILATION_X, DILATION_Y, DEPTHWISE],
intrinsic(name='transpose',
         src_comp=[-1, -1], # Srcs: InputTensorHandle, OutputTensorHandle
         dest_comp=-1,  # No SSA destination; output is via writing to OutputTe
         indices=[PERMUTATION],
```



Program generation: convolutions



Program generation: tensor additions

```
nir_def *input_0_src = tensor_to_nir(tf_context, b, "input_feature_map_0", node->input
nir_def *input_1_src = tensor_to_nir(tf_context, b, "input_feature_map_1", node->input
nir_def *output_src = tensor_to_nir(tf_context, b, "output_feature_map", node->outputs
nir_tensor_add(b, input_0_src, input_1_src, output_src);
```



Compiler passes: ensure NCHW

```
etna ensure nchw(nir shader *psubgraph, struct etna ml subgraph *subgraph)
   bool progress = false;
   nir_foreach_function_impl(impl, psubgraph) {
      nir builder b = nir builder create(impl);
      bool func progress = false;
      nir_foreach_block(block, impl) {
         nir foreach instr(instr, block) {
            if (instr->type == nir instr type intrinsic) {
               nir_intrinsic_instr *intr = nir_instr as_intrinsic(instr);
               switch(intr->intrinsic) {
                  case nir_intrinsic_conv2d: {
                     bool input channels last = etna_ml_qet_tensor_desc(intr->src[0].ssa)->chan
                     bool output channels last = etna ml get tensor desc(intr->src[3].ssa)->cha
                     if (input channels last) {
                        /* The tensor is in channel-last, but the hardware needs channel-first
                        add_transpose(subgraph, &b, intr, 0, true);
                        func progress = true;
```



Compiler passes: ensure NCHW (2)

```
static void
add_transpose(struct etna_ml_subgraph *subgraph, nir_builder *b, nir_intrinsic_instr *intr,
   b->cursor = nir_before_instr(&intr->instr);
   nir_def *interm_tensor = create_tensor(subgraph, b, intr->src[src_idx].ssa, false);
   if (last to first) {
      b->cursor = nir_before_instr(&intr->instr);
      nir_transpose(b, intr->src[src_idx].ssa, interm_tensor, .permutation = {0, 3, 1, 2});
     else {
      b->cursor = nir_after_instr(&intr->instr);
      nir_transpose(b, interm_tensor, intr->src[src_idx].ssa, .permutation = {0, 2, 3, 1});
   nir src rewrite(&intr->src[src idx], interm tensor);
```



Compiler passes: remove dead transposes

```
bool
etna_dead_transposes(nir_shader *psubgraph, struct etna_ml_subgraph *subgraph)
   bool progress = false;
   nir_function_impl *impl = nir_shader_get_entrypoint(psubgraph);
   for_each_transpose_safe(impl) {
      nir_intrinsic_instr *intr = nir_instr_as_intrinsic(instr);
      struct glsl_permutation perm = nir intrinsic permutation(intr);
      unsigned output_idx = tensor_idx_from_src(instr, 1);
      bool can be removed = true;
      bool first_to_last = perm.dims[0] == 0 &&
                           perm.dims[1] == 2 &&
                           perm.dims[2] == 3 &&
                           perm.dims[3] == 1;
      struct util_dynarray candidates = {0};
      util_dynarray_init(&candidates, NULL);
      for_each_consumer(impl, output_idx) {
         if (!check_dead_transposes(impl, instr, first_to_last, &candidates)) {
            can_be_removed = false;
            break;
```

Compiler passes: remove dead transposes (2)

```
if (can_be_removed && util_dynarray_num_elements(&candidates, nir_instr *)) {
      nir_def_rewrite_uses(intr->src[1].ssa, intr->src[0].ssa);
      nir instr remove(&intr->instr);
      util_dynarray_foreach(&candidates, nir_instr *, instr) {
         nir intrinsic instr *transpose = nir instr as intrinsic(*instr);
         nir_def_rewrite_uses(transpose->src[1].ssa, transpose->src[0].ssa);
         nir_instr_remove(&transpose->instr);
  util_dynarray_fini(&candidates);
nir_progress(progress, impl, nir_metadata_none);
return progress;
```

Compiler passes: lower strided convolution

- A particular NPU might not support strided convolutions natively
- It has been proved that a strided convolution can be lowered to a normal one without any loss in accuracy
- There may be performance implications, but the results should be the same
- We can provide a HW-independent lowering pass that replaces all strided convolutions with regular ones, for drivers to use as needed
- See the implementation in the merge request

Why doing all this with NIR?

- We need infrastructure to create several IRs:
 - one to represent the operations that ML frameworks give to us, which
 we can use for lowering to hardware-specific IRs but also for common
 optimizations and lowering passes,
 - at least one per driver to lower to something closer to the HW, for performing further optimization passes and in some cases to lower further, and
 - some drivers will need one more IR before hardware instructions can be generated.



Why doing all this with NIR? (2)

- If we didn't have NIR yet, we would need to write it anyway (and maintain it!)
- Vulkan drivers are probably going to need at some point to implement extensions with operations on tensors
- Seems like NIR can be extended in this direction with little disruption?



Questions

- Or you can also ask in #ml-mainline at OFTC
- Or feel free to ask Philipp or Tomeu any time after this talk

