EECS 498 Final Project

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Optimization1: Unroll + shared-memory Matrix multiply (Abandoned)

We first implemented the suggested optimization Unroll + shared-memory Matrix multiply.

The unrolling step does the index mapping and stores the unrolling matrix. And this step can transfer the convolution problem into the matrix multiply problem. The kernel for **Unroll** imitates the code shown in lecture 19, page 34. Note that in the slide, the values for w_unroll and h_unroll are incorrect. The correct value should be

```
int w_unroll = h_out * W_out + w_out;
int h_unroll = c * K * K + p * K + q;
```

In the **shared-memory matrix multiply** step, we used the kernel in the HW3 Tiled Matrix Multiplication. Both the weight matrix and unrolled x are loaded into shared memory before computation.

Initially, we set the TILE_WIDTH = 32 (for matrix multiply) and BLOCK_SIZE = 128 (for unroll). The run time for both layers is 0.170043 and 0.406344 separately.

The screenshot of the output given TILE_WIDTH = 32 and BLOCK_SIZE = 128:

```
New Inference
Op Time: 0.170043
Op Time: 0.406344
Correctness: 0.7955 Model: eecs498
≔182719== Profiling application: python submit/submission.py
 ≔182719== Profiling result:
                                                                Min
                  Time (%)
                                         Calls
            Type
                                Time
                                                      Avg
 GPU activities:
                   60. 52%
                            409.60ms
                                         20000
                                                20. 480us
                                                           7.8400us
           mxnet::op::gemm(float*, float*, float*, int, int)
 36. 063us
                                         20000 6. 5010us
                    19. 21%
                            130.03ms
                                                           5. 5360us
 9. 8240us
           mxnet::op::unroll(float const *, float*, int, int, int,
 int, int, int,
                int, int,
                           int)
                    16. 30%
                           110. 35ms
                                            20
                                                5. 5174ms
                                                           1.0880us
 108. 22ms
           [CUDA memcpy HtoD]
```

The next optimization we tried was **Sweeping various parameters to find best values**. We use grid search to find the best hyperparameter: TILE_WIDTH and BLOCK_SIZE. The result is shown in the following table. We found that when TILE_WIDTH = 16 and BLOCK_SIZE = 128, the speed is fastest. But it still did not achieve the goal (under 0.3 seconds for both layers combined).

TILE_WIDTH	BLOCK_SIZE	OP Time 1	OP Time 2
16	64	0.148216	0.339553
16	128	0.136755	0.289244
16	256	0.140186	0.293229
16	512	0.146108	0.305463
32	64	0.160920	0.453823
32	128	0.170043	0.406344
32	256	0.171340	0.407562
32	512	0.170779	0.418037

Since there are too many outputs in the table, we decided to put only one screenshot in the report. The screenshot of the output given TILE_WIDTH = 16 and BLOCK_SIZE = 128:

```
New Inference
Op Time: 0.136755
Op Time: 0.289244
Correctness: 0.7955 Model: eecs498
 =157427== Profiling application: python submit/submission.py
 =157427== Profiling result:
                                 Time
             Type
                   Time (%)
                                           Calls
                                                        Avg
                                                                   Min
      Max
                    50.01%
                                           20000
 GPU activities:
                             263. 43ms
                                                  13. 171us
                                                             5. 4080us
           mxnet::op::gemm(float*, float*, float*, int,
 25. 152us
                    24. 09%
                             126.89ms
                                           20000 6. 3440us
                                                             5. 6320us
 9.5040us
           mxnet::op::unroll(float const *, float*, int,
                                                             int, int,
           int, int, int, int)
20.80% 109
 int, int,
                             109.56ms
                                              20
                                                   5. 4781ms
                                                              1. 1830us
            [CUDA memcpy HtoD]
 107. 42ms
```

Optimization2: Kernel fusion for unrolling and matrixmultiplication (Abandoned)

Then we tried to implement **Kernel fusion for unrolling and matrix-multiplication**. The implementation detail is that instead of launching a kernel to unroll the input x and having a separate matrix to store the unrolled x, we directly calculate the correct index when loading the input into the shared memory in the matrix multiplication step.

Unexpectedly, we found that the run time became larger in the second convolution layer. The possible reason is that getting the correct index requires lots of calculations, so it is better to launch the unrolling kernel and do it concurrently.

The screenshot of the output:

```
New Inference
Op Time: 0.081066
Op Time: 0.368898
Correctness: 0.7955 Model: eecs498
 =200445== Profiling application: python submit/submission.py
==200445== Profiling result:
                               Time
            Type
                  Time (%)
                                         Calls
                                                     Avg
      Max
           Name
GPU activities:
                   75. 74% 432. 61ms
                                         20000
                                                21. 630us 6. 5920us
39.008us mxnet::op::matrixMultiplyShared_Unroll(float*,
float*, int, int, int, int, int, int)
                   19.51% 111.46ms
                                                5. 5728ms
                                                          1. 1200us
           [CUDA memcpy HtoD]
109. 29ms
```

Optimization3: Shared Memory convolution

Since global memory read and global memory write are quite slow, this optimization utilizes the shared memory to have several threads share the local version of data. Both the weight matrix and input data x are loaded into shared memory before computation.

The forward kernel for **Shared Memory convolution** imitates the code shown in lecture 19, page 28. We also added more boundary checks to avoid invalid memory access. We found two mistakes in the slide.

In the step of loading tiles from input data x into shared memory, the correct code should be

```
X_{shared[i - h_base, j - w_base]} = x4d(b, c, i, j);
```

instead of

```
X_{shared[i - h_base, j - w_base]} = x4d(b, c, h, w);
```

And in the step of doing convolution, , the correct code should be

```
acc += X_shared[h0 + p, w0 + q] * W_shared[p, q];
```

instead of

```
acc += X_shared[h + p, w + q] * W_shared[p, q];
```

The screenshot of the output:

```
New Inference
Op Time: 0.120604
Op Time: 0.237765
Correctness: 0.7955 Model: eecs498
 =47777== Profiling application: python submit/submission.py
 =47777== Profiling result:
                   Time(%)
                                Time
                                          Calls
                                                                 Min
             Type
                                                       Avg
      Max
           Name
 GPU activities:
                    72. 24% 358. 26ms
                                              2
                                                 179. 13ms
                                                            120. 56ms
           mxnet::op::ConvLayerForward(float*, float const *, floa
 237. 70ms
                      int, int, int, int)
                    22. 31%
                            110.65ms
                                             20 5. 5324ms
                                                            1. 0880us
 108.51ms [CUDA memcpy HtoD]
```

Optimization4: Weight matrix (kernel values) in constant memory

Since the weight matrix keeps unchanged during the computation, it is feasible to load it into constant memory. And when the weight matrix is loaded into constant memory, there is no need to load it into shared memory, which can accelerate the kernel.

The size of weight matrix is MCK^2 . For the first convolution layer, M=12, C=1, K=7. For the second convolution layer, M=24, C=12, K=7.

We set the weight matrix in constant memory as

```
__constant__ float deviceKernel[14112];
```

```
,where 14112 = 24 \times 12 \times 7^2.
```

The forward kernel is almost the same as the one in **Shared Memory convolution**. The main difference is that it saves the step to load the weight matrix into shared memory, and it directly uses the weight matrix in constant memory when calculating convolution.

After that optimization, it finally achieves the goal (under 0.3 seconds for both layers combined)!

The screenshot of the output:

```
New Inference
Op Time: 0.092234
Op Time: 0.193077
Correctness: 0.7955 Model: eecs498
 =218065== Profiling application: python submit/submission.py
 =218065== Profiling result:
                                          Calls
                                                                 Min
                  Time (%)
                                Time
            Type
                                                       Avg
      Max
 GPU activities:
                    67. 39%
                                                 142. 58ms
                            285. 16ms
                                                            92. 139ms
           mxnet::op::ConvLayerForward(float*, float const *, int,
 193. 02ms
                int, int)
 int, int, int,
                            111.05ms
                                             20
                                                 5. 5526ms
                                                            1. 1200us
                    26. 24%
           [CUDA memcpy HtoD]
 108. 92ms
```

Appendix

The source code for Unroll + shared-memory Matrix multiply

```
#ifndef MXNET_OPERATOR_NEW_FORWARD_CUH_
#define MXNET_OPERATOR_NEW_FORWARD_CUH_

#include <mxnet/base.h>

#define TILE_WIDTH 16
#define BLOCK_SIZE 128

namespace mxnet
{
    namespace op
```

```
__global__ void gemm(float *A, float *B, float *C, int numARows, int
numAColumns, int numBColumns) {
  __shared__ float subTileA[TILE_WIDTH][TILE_WIDTH];
   _shared__ float subTileB[TILE_WIDTH][TILE_WIDTH];
  int bx = blockIdx.x; int by = blockIdx.y;
  int tx = threadIdx.x; int ty = threadIdx.y;
  int Row = by * TILE_WIDTH + ty;
  int Col = bx * TILE_WIDTH + tx;
  float temp = 0;
  for(int m = 0; m < ceil((float)numAColumns/TILE_WIDTH); m++){</pre>
    if(Row < numARows && m * TILE_WIDTH + tx < numAColumns)</pre>
      subTileA[ty][tx] = A[Row * numAColumns + m * TILE_WIDTH + tx]; //A[Row][m]
* TILE_WIDTH + tx]
    else
      subTileA[ty][tx] = 0;
    if(m * TILE_WIDTH + ty < numAColumns && Col < numBColumns)</pre>
      subTileB[ty][tx] = B[(m * TILE_WIDTH + ty) * numBColumns + Col]; //B[m *
TILE_WIDTH + ty][Co]]
    else
      subTileB[ty][tx] = 0;
    __syncthreads();
    for(int k = 0; k < TILE_WIDTH; k++){
      temp += subTileA[ty][k] * subTileB[k][tx];
   }
    __syncthreads();
  }
  if(Row < numARows && Col < numBColumns)</pre>
   C[Row * numBColumns + Col] = temp;
}
__global__ void unroll(const float *x, float *x_unroll, int b, const int C,
const int H, const int W, const int K, int H_out, int W_out, int H_unroll, int
W_unroll) {
#define x4d(i3, i2, i1, i0) x[(i3) * (C * H * W) + (i2) * (H * W) + (i1) * (W) +
    int idx = blockIdx.x * blockDim.x + threadIdx.x;
    if (idx < C * W_unroll) {</pre>
        int c = idx / W_unroll;
        int s = idx % W_unroll;
        int h_out = s / W_out;
        int w_out = s % W_out;
        int w_unroll = h_out * W_out + w_out;
        for (int p = 0; p < K; p++) {
            for (int q = 0; q < K; q++) {
                int h_{unroll} = c * K * K + p * K + q;
                x_{unroll} = x4d(b, c, h_{out} + p,
w_out + q);
            }
        }
#undef x4d
```

```
void ConvLayerForward(float *y, float *x, float *k, int B, int M, int C, int H,
int W, int K){
    int H_{out} = H - K + 1;
    int W_{out} = W - K + 1;
    int H_unroll = C * K * K;
    int W_unroll = H_out * W_out;
    //int numARows = M;
   //int numAColumns = H_unroll;
   //int numBColumns = W_unroll;
   //int numBRows = numAColumns;
   //int numCRows = numARows;
    //int numCColumns = numBColumns;
    dim3 dimGrid1(ceil((float)H_unroll * W_unroll/BLOCK_SIZE), 1, 1);
    dim3 dimBlock1(BLOCK_SIZE, 1, 1);
    dim3 dimGrid2(ceil((float)W_unroll/TILE_WIDTH), ceil((float)M/TILE_WIDTH),
1);
    dim3 dimBlock2(TILE_WIDTH, TILE_WIDTH, 1);
    float *x_unroll;
    cudaMalloc((void **) &x_unroll, H_unroll * W_unroll * sizeof(float));
    for(int b = 0; b < B; b++){
        unroll <<< dimGrid1, dimBlock1>>>> (x, x_unroll, b, C, H, W, K, H_out,
W_out, H_unroll, W_unroll);
        gemm<<<dimGrid2, dimBlock2>>>(k, x_unroll, &y[b*M*H_out*W_out], M,
H_unroll, W_unroll);
    cudaFree(x_unroll);
}
  This function is called by new-inl.h
  Any code you write should be executed by this function.
  We only expect the float version of the operator to be called, so here we
specialize with only floats.
*/
template <>
void forward<gpu, float>(mshadow::Tensor<gpu, 4, float> &y, const
mshadow::Tensor<gpu, 4, float> &x, const mshadow::Tensor<gpu, 4, float> &w)
{
    // // Use mxnet's CHECK_EQ to do assertions.
   // CHECK_EQ(0, 1)
    const int B = x.shape_[0];
    const int M = y.shape_[1]; // num_filter
    const int C = x.shape_[1];
    const int H = x.shape_[2];
    const int W = x.shape_[3];
    const int K = w.shape_[3];
    MSHADOW_CUDA_CALL(cudaDeviceSynchronize());
    ConvLayerForward(y.dptr_, x.dptr_, w.dptr_, B, M, C, H, W, K);
```

```
MSHADOW_CUDA_CALL(cudaDeviceSynchronize());
}

/*
    This tells mxnet how to do an op when it's not a float.
    This is not used in the project

*/
template <typename gpu, typename DType>
void forward(mshadow::Tensor<gpu, 4, DType> &y, const mshadow::Tensor<gpu, 4, DType> &x, const mshadow::Tensor<gpu, 4, DType> &w)
{
    assert(0 && "No forward implementation for other datatypes needed");
}
}
#endif
```

The source code for Kernel fusion for unrolling and matrix-multiplication

```
#ifndef MXNET_OPERATOR_NEW_FORWARD_CUH_
#define MXNET_OPERATOR_NEW_FORWARD_CUH_
#include <mxnet/base.h>
#define TILE_WIDTH 16
#define BLOCK_SIZE 128
namespace mxnet
{
namespace op
__global__ void matrixMultiplyShared_Unroll(float *kernel, float *x, float *y,
                                      int numARows, int numAColumns, int
numBColumns,
                                      int C, int K, int H, int W) {
  __shared__ float subTileA[TILE_WIDTH][TILE_WIDTH];
  __shared__ float subTileB[TILE_WIDTH][TILE_WIDTH];
 int bx = blockIdx.x; int by = blockIdx.y;
  int tx = threadIdx.x; int ty = threadIdx.y;
  int Row = by * TILE_WIDTH + ty;
  int Col = bx * TILE_WIDTH + tx;
  int W_{out} = W - K + 1;
  int w = Col % W_out;
  int h = Col / W_out;
  float temp = 0;
  for(int m = 0; m < ceil((float)numAColumns/TILE_WIDTH); m++){</pre>
    if(Row < numARows && m * TILE_WIDTH + tx < numAColumns)</pre>
      subTileA[ty][tx] = kernel[Row * numAColumns + m * TILE_WIDTH + tx];
//A[Row][m * TILE_WIDTH + tx]
   else
      subTileA[ty][tx] = 0;
```

```
int h_unroll = m * TILE_WIDTH + ty;
    if(h_unroll < numAColumns && Col < numBColumns){</pre>
     int q = h_unroll % K;
      h_unroll /= K;
     int p = h_unroll % K;
     int c = h_unroll / K;
     subTileB[ty][tx] = x[c * (H * W) + (h+p) * (W) + W+q];
    }
    else
     subTileB[ty][tx] = 0;
    __syncthreads();
   for(int k = 0; k < TILE_WIDTH; k++){
      temp += subTileA[ty][k] * subTileB[k][tx];
   }
    __syncthreads();
  if(Row < numARows && Col < numBColumns)</pre>
   y[Row * numBColumns + Col] = temp;
}
void convLayer_forward(float *y, float *x, float *k, int B, int M, int C, int H,
int W, int K){
   int H_{out} = H - K + 1;
   int W_{out} = W - K + 1;
   int H_{unroll} = C * K * K;
   int W_unroll = H_out * W_out;
    dim3 dimGrid(ceil((float)W_unroll/TILE_WIDTH), ceil((float)M/TILE_WIDTH),
1);
    dim3 dimBlock(TILE_WIDTH, TILE_WIDTH, 1);
    for(int b = 0; b < B; b++){
        matrixMultiplyShared_Unroll<<<dimGrid, dimBlock>>>(k, &x[b*C*H*W],
&y[b*M*H_out*W_out], M, H_unroll, W_unroll,C,K,H,W);
}
  This function is called by new-inl.h
  Any code you write should be executed by this function.
   We only expect the float version of the operator to be called, so here we
specialize with only floats.
*/
template <>
void forward<gpu, float>(mshadow::Tensor<gpu, 4, float> &y, const
mshadow::Tensor<gpu, 4, float> &x, const mshadow::Tensor<gpu, 4, float> &w)
{
    // // Use mxnet's CHECK_EQ to do assertions.
    // CHECK_EQ(0, 1)
    const int B = x.shape_[0];
```

```
const int M = y.shape_[1]; // num_filter
    const int C = x.shape_[1];
    const int H = x.shape_[2];
    const int W = x.shape_[3];
    const int K = w.shape_[3];
    MSHADOW_CUDA_CALL(cudaDeviceSynchronize());
    convLayer_forward(y.dptr_, x.dptr_, w.dptr_, B, M, C, H, W, K);
    MSHADOW_CUDA_CALL(cudaDeviceSynchronize());
}
   This tells mxnet how to do an op when it's not a float.
   This is not used in the project
*/
template <typename gpu, typename DType>
void forward(mshadow::Tensor<gpu, 4, DType> &y, const mshadow::Tensor<gpu, 4,
DType> &x, const mshadow::Tensor<gpu, 4, DType> &w)
{
    assert(0 && "No forward implementation for other datatypes needed");
}
}
}
#endif
```

The source code for shared Memory convolution

```
#ifndef MXNET_OPERATOR_NEW_FORWARD_CUH_
#define MXNET_OPERATOR_NEW_FORWARD_CUH_
#include <mxnet/base.h>
#define TILE_WIDTH 32
namespace mxnet
{
namespace op
__global__ void ConvLayerForward(float *y, const float *x, const float *k, const
int B, const int M, const int C, const int H, const int W, const int K)
{
#define y4d(i3, i2, i1, i0) y[(i3) * (M * H_out * W_out) + (i2) * (H_out * W_out)
+ (i1) * (W_out) + i0]
#define x4d(i3, i2, i1, i0) x[(i3) * (C * H * W) + (i2) * (H * W) + (i1) * (W) +
#define k4d(i3, i2, i1, i0) k[(i3) * (C * K * K) + (i2) * (K * K) + (i1) * (K) +
i0]
    const int H_{out} = H - K + 1;
    const int W_{out} = W - K + 1;
    int W_grid = ceil((float)W_out/TILE_WIDTH);
```

```
int H_grid = ceil((float)H_out/TILE_WIDTH);
    int X_TILE_WIDTH = TILE_WIDTH + K - 1;
    extern __shared__ float shmem[];
    float* sharedX = &shmem[0];
   float* sharedw = &shmem[X_TILE_WIDTH * X_TILE_WIDTH];
   int b = blockIdx.x;
   int m = blockIdx.y;
   int h0 = threadIdx.x;
   int w0 = threadIdx.y;
   int h_base = (blockIdx.z / w_grid) * TILE_WIDTH;
   int w_base = (blockIdx.z % W_grid) * TILE_WIDTH;
   int h = h_base + h0;
   int w = w_base + w0;
   float acc = 0.0;
   for (int c = 0; c < C; c++) {
        if(h0 < K \&\& w0 < K)
            sharedw[h0 * K + w0] = k4d(m, c, h0, w0);
        __syncthreads();
        for (int i = h; i < h_base + X_TILE_WIDTH; i += TILE_WIDTH) {</pre>
            for (int j = w; j < w_base + X_TILE_WIDTH; j += TILE_WIDTH) {
               if(i < H \&\& j < W)
                   sharedX[(i - h_base) * X_TILE_WIDTH + (j - w_base)] = x4d(b,
c, i, j);
               else
                   sharedX[(i - h_base) * X_TILE_WIDTH + (j - w_base)] = 0;
           }
        __syncthreads();
       for (int p = 0; p < K; p++) {
            for (int q = 0; q < K; q++) {
               acc += sharedx[(h0 + p) * X_TILE_WIDTH + (w0 + q)] *
sharedw[p * K + q];
           }
        __syncthreads();
   if(b < B \&\& m < M \&\& h < H_out \&\& w < W_out)
        y4d(b, m, h, w) = acc;
#undef y4d
#undef x4d
#undef k4d
}
/*
  This function is called by new-inl.h
  Any code you write should be executed by this function.
  We only expect the float version of the operator to be called, so here we
specialize with only floats.
*/
template <>
```

```
void forward<gpu, float>(mshadow::Tensor<gpu, 4, float> &y, const
mshadow::Tensor<gpu, 4, float> &x, const mshadow::Tensor<gpu, 4, float> &w)
    // // Use mxnet's CHECK_EQ to do assertions.
    // CHECK_EQ(0, 1)
    const int B = x.shape_[0];
    const int M = y.shape_[1]; // num_filter
    const int C = x.shape_[1];
    const int H = x.shape_[2];
    const int W = x.shape_[3];
    const int K = w.shape_[3];
    const int H_{out} = H - K + 1;
    const int W_{out} = W - K + 1;
    int W_grid = ceil((float)W_out/TILE_WIDTH);
    int H_grid = ceil((float)H_out/TILE_WIDTH);
    int X_TILE_WIDTH = TILE_WIDTH + K - 1;
    size_t shared_size = sizeof(float) * (X_TILE_WIDTH*X_TILE_WIDTH+K*K);
    dim3 dimBlock(TILE_WIDTH, TILE_WIDTH, 1);
    dim3 dimGrid(B, M, H_grid * W_grid);
    MSHADOW_CUDA_CALL(cudaDeviceSynchronize());
    ConvLayerForward<<<dimGrid, dimBlock, shared_size>>>(y.dptr_, x.dptr_,
w.dptr_, B, M, C, H, W, K);
    MSHADOW_CUDA_CALL(cudaDeviceSynchronize());
}
   This tells mxnet how to do an op when it's not a float.
   This is not used in the project
*/
template <typename gpu, typename DType>
void forward(mshadow::Tensor<gpu, 4, DType> &y, const mshadow::Tensor<gpu, 4,
DType> &x, const mshadow::Tensor<gpu, 4, DType> &w)
{
    assert(0 && "No forward implementation for other datatypes needed");
}
}
#endif
```

The source code for shared Memory convolution & Weight matrix (kernel values) in constant memory

```
#ifndef MXNET_OPERATOR_NEW_FORWARD_CUH_
#define MXNET_OPERATOR_NEW_FORWARD_CUH_
#include <mxnet/base.h>
```

```
#define TILE_WIDTH 32
namespace mxnet
{
namespace op
__constant__ float deviceKernel[14112];
__global__ void ConvLayerForward(float *y, const float *x, const int B, const
int M, const int C, const int H, const int W, const int K)
#define y4d(i3, i2, i1, i0) y[(i3) * (M * H_out * W_out) + (i2) * (H_out * W_out)
+ (i1) * (W_out) + i0]
#define x4d(i3, i2, i1, i0) x[(i3) * (C * H * W) + (i2) * (H * W) + (i1) * (W) +
#define k4d(i3, i2, i1, i0) k[(i3) * (C * K * K) + (i2) * (K * K) + (i1) * (K) +
#define const_k4d(i3, i2, i1, i0) deviceKernel[(i3) * (C * K * K) + (i2) * (K *
(K) + (i1) * (K) + i0
    const int H_{out} = H - K + 1;
    const int W_{out} = W - K + 1;
    int W_grid = ceil((float)W_out/TILE_WIDTH);
    int H_grid = ceil((float)H_out/TILE_WIDTH);
    int X_TILE_WIDTH = TILE_WIDTH + K - 1;
    extern __shared__ float shmem[];
    float* sharedX = &shmem[0];
    //float* sharedw = &shmem[X_TILE_WIDTH * X_TILE_WIDTH];
    int b = blockIdx.x;
    int m = blockIdx.y;
    int h0 = threadIdx.x;
    int w0 = threadIdx.y;
    int h_base = (blockIdx.z / W_grid) * TILE_WIDTH;
    int w_base = (blockIdx.z % W_grid) * TILE_WIDTH;
    int h = h_base + h0;
    int w = w_base + w0;
    float acc = 0.0;
    for (int c = 0; c < C; c++) {
        for (int i = h; i < h_base + X_TILE_WIDTH; i += TILE_WIDTH) {</pre>
            for (int j = w; j < w_base + X_TILE_WIDTH; j += TILE_WIDTH) {</pre>
                if(i < H \&\& j < W)
                    sharedX[(i - h\_base) * X\_TILE\_WIDTH + (j - w\_base)] = x4d(b,
c, i, j);
                else
                    sharedX[(i - h\_base) * X\_TILE\_WIDTH + (j - w\_base)] = 0;
        __syncthreads();
        for (int p = 0; p < K; p++) {
            for (int q = 0; q < K; q++) {
                if(h0 + p < X_TILE_WIDTH \& w0 + q < X_TILE_WIDTH)
```

```
//acc += sharedx[(h0 + p) * X_TILE_WIDTH + (w0 + q)] *
sharedw[p * K + q];
                    acc += sharedX[(h0 + p) * X_TILE_WIDTH + (w0 + q)] *
const_k4d(m, c, p, q);
        }
         __syncthreads();
    if(b < B \& m < M \& h < H_out \& w < W_out)
        y4d(b, m, h, w) = acc;
#undef y4d
#undef x4d
#undef k4d
#undef const_k4d
}
   This function is called by new-inl.h
  Any code you write should be executed by this function.
   We only expect the float version of the operator to be called, so here we
specialize with only floats.
*/
template <>
void forward<qpu, float>(mshadow::Tensor<qpu, 4, float> &y, const
mshadow::Tensor<gpu, 4, float> &x, const mshadow::Tensor<gpu, 4, float> &w)
    // // Use mxnet's CHECK_EQ to do assertions.
    // CHECK_EQ(0, 1)
    const int B = x.shape_[0];
    const int M = y.shape_[1]; // num_filter
    const int C = x.shape_[1];
   const int H = x.shape_[2];
    const int W = x.shape_[3];
    const int K = w.shape_[3];
    const int H_{out} = H - K + 1;
    const int W_{out} = W - K + 1;
    int W_grid = ceil((float)W_out/TILE_WIDTH);
    int H_grid = ceil((float)H_out/TILE_WIDTH);
    int X_TILE_WIDTH = TILE_WIDTH + K - 1;
    size_t shared_size = sizeof(float) * (X_TILE_WIDTH*X_TILE_WIDTH);
    dim3 dimBlock(TILE_WIDTH, TILE_WIDTH, 1);
    dim3 dimGrid(B, M, H_grid * W_grid);
    cudaMemcpyToSymbol(deviceKernel, w.dptr_, (M*C*K*K) * sizeof(float));
    MSHADOW_CUDA_CALL(cudaDeviceSynchronize());
    ConvLayerForward<<<dimGrid, dimBlock, shared_size>>>(y.dptr_, x.dptr_, B, M,
C, H, W, K);
    MSHADOW_CUDA_CALL(cudaDeviceSynchronize());
}
```

```
This tells mxnet how to do an op when it's not a float.
This is not used in the project

*/

template <typename gpu, typename DType>

void forward(mshadow::Tensor<gpu, 4, DType> &y, const mshadow::Tensor<gpu, 4,

DType> &x, const mshadow::Tensor<gpu, 4, DType> &w)

{
    assert(0 && "No forward implementation for other datatypes needed");
}

#endif
```