

Obsidian: GPU Kernel Programming in Haskell

Licentiate Seminar

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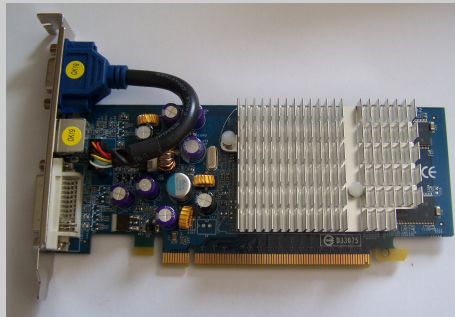
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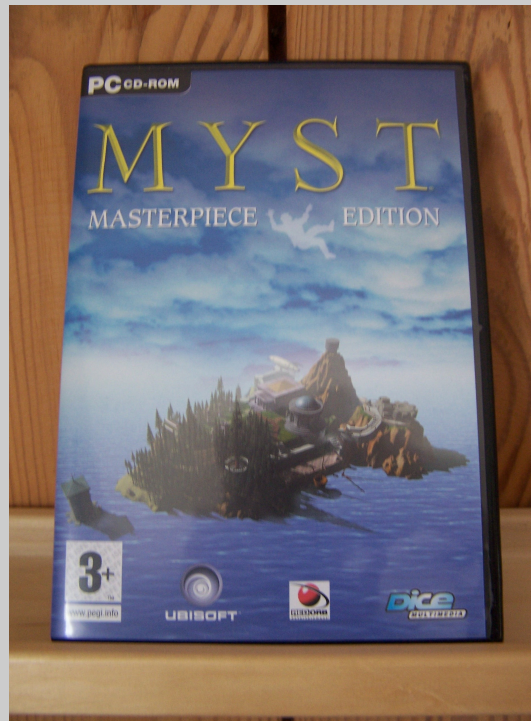
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GPUs



GPUs

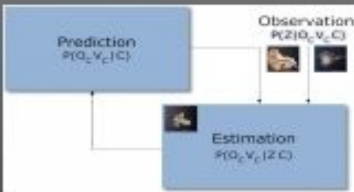
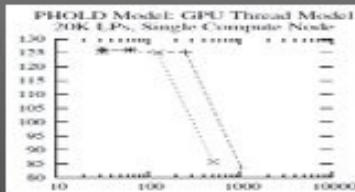
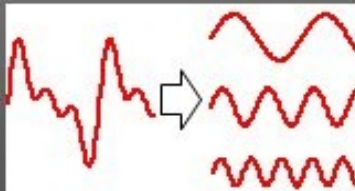
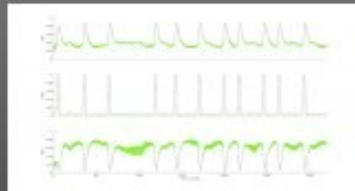
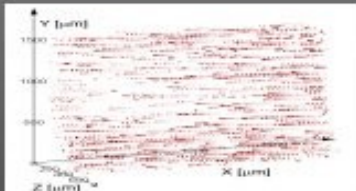
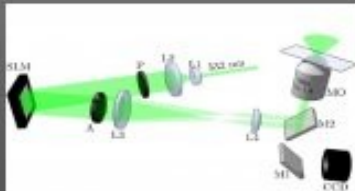




GPUs



General Purpose Computations on GPUs (the GPGPU field)

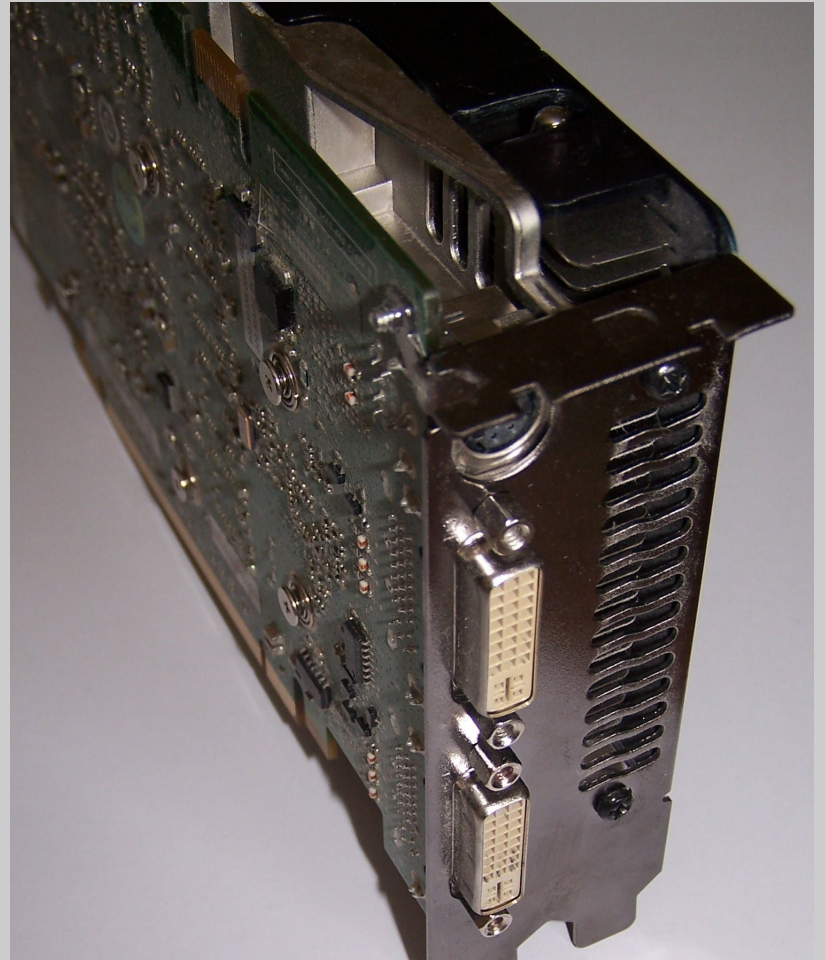
 Bayesian Real-Time Perception Algorithms on GPU 1000 x	 Fast Total Variation for Computer Vision 1000 x	 AN APPROACH FOR THE EFFECTIVE UTILIZATION OF GP-GP... 539 x	 Cubic Interpolation 327 x	 Furry Ball: GPU renderer for Maya 300 x
 Real Time Elimination of Undersampling Artifacts i... 2300 x	 Fast and Exact Solution of Total Variation Models ... 1000 x	 Tool for Generalized Harmonics Analysis 420 x	 Synthetic Aperture Radar Back-Projection Algorithm 300 x	 Data Assimilation using a GPU Accelerated Path Int... 300 x
 Computer Generated Hologram on GPU - Simple color ... 1500 x	 Flow dynamics measurements using digital holograph... 1000 x	 Real-time optical manipulation of micron sized str... 350 x	 Monte Carlo eXtreme (MCX) 300 x	 Accelerating total variation regularization for ma... 100 x

GPGPU

- Use graphics processors for things not directly graphics related.
- Evolving area.
 - Used to be hard: “exploit” the graphics API in clever ways to make the GPU compute something
 - Greatly improved by high-level languages such as NVIDIA CUDA
- GPUs are still hard to program

NVIDIA CUDA

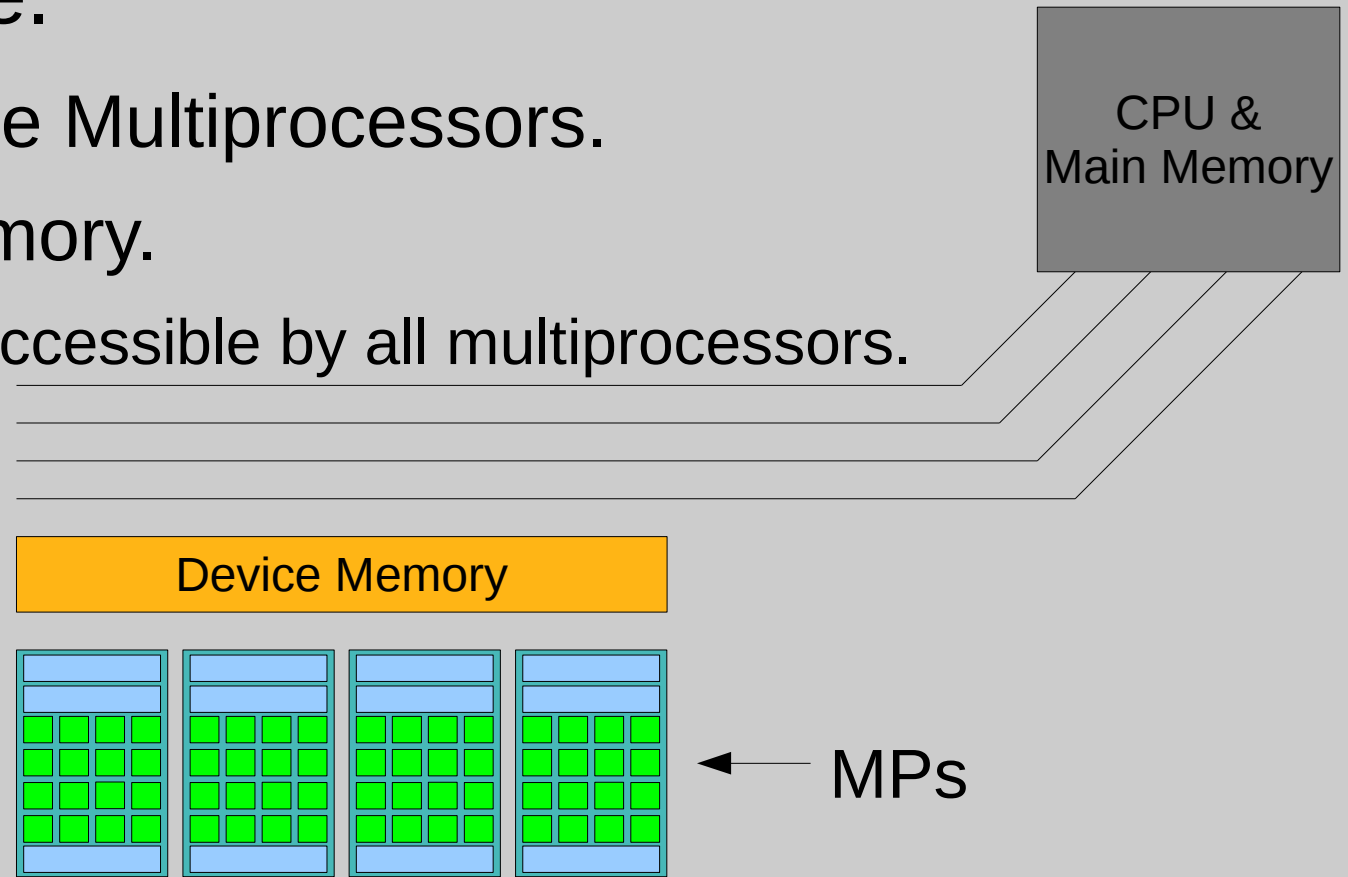
- Compute Unified Device Architecture
 - Architecture and programming model of modern NVIDIA GPUs.



GFX-Card with 8800 series GPU

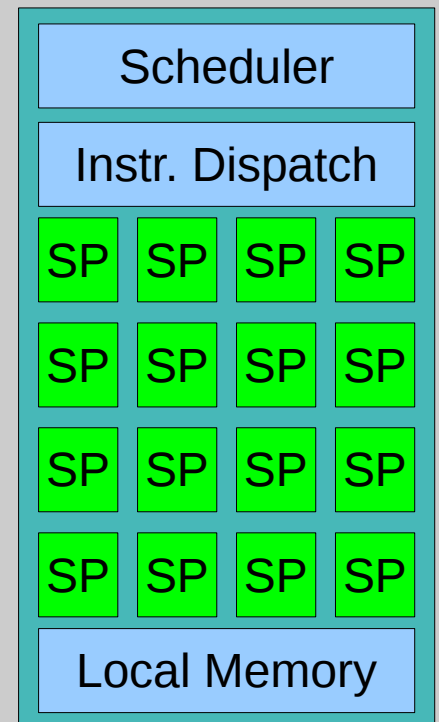
CUDA Architecture

- A CUDA GPU is based on a scalable architecture.
 - One or more Multiprocessors.
 - Device memory.
 - Memory accessible by all multiprocessors.



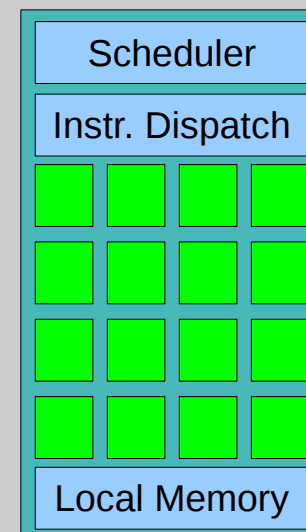
Close up on a Multiprocessor

- One MP corresponds to what people often call a “core”.
 - Has a number of processing units (SP).
 - SIMD style.
 - 8, 32 SPs (Now called “CUDA cores”)
 - Local memory accessible by the SPs.
 - Kilobytes
 - Multithreading, handled by scheduler.
 - Hundreds of threads per MP

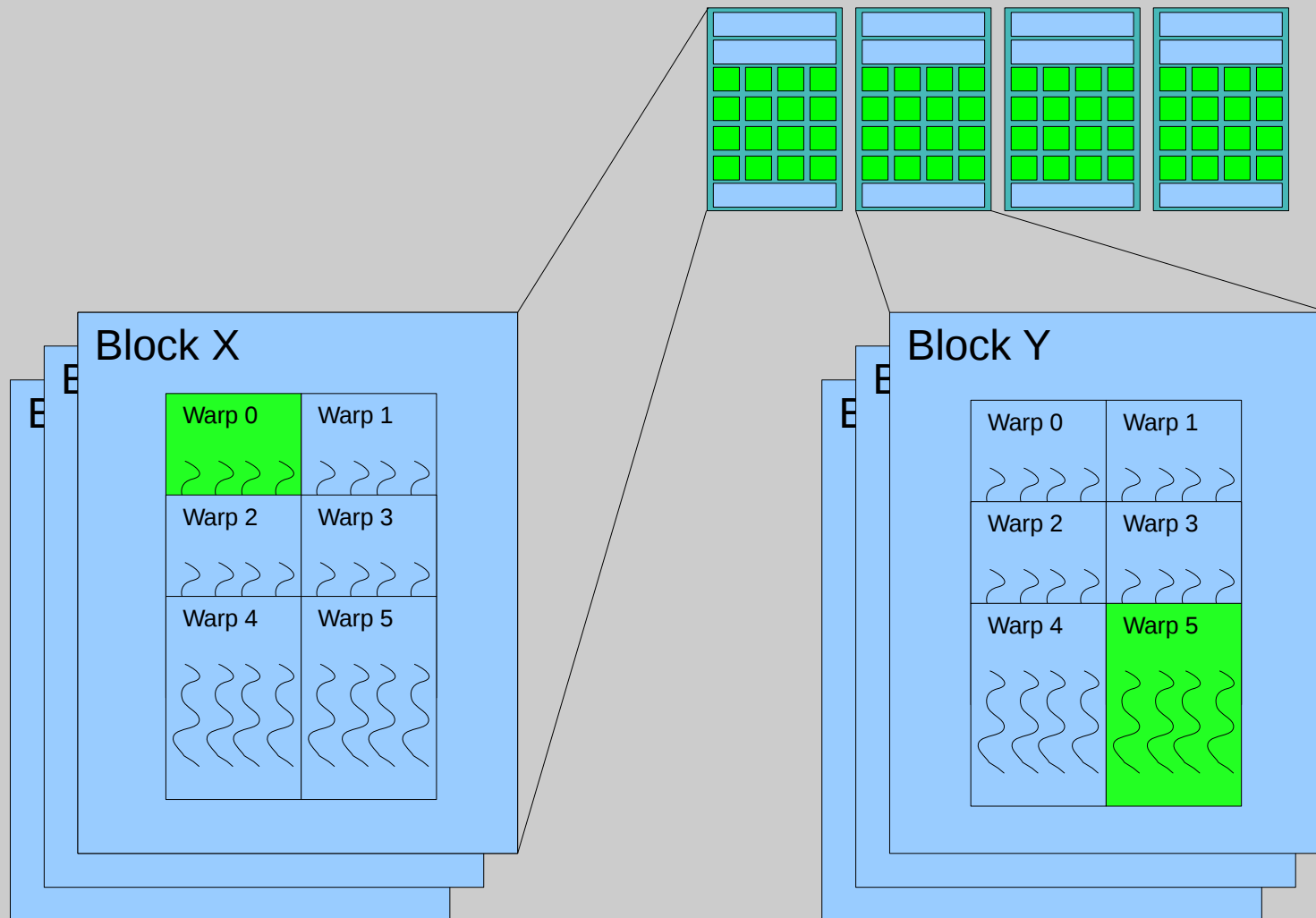


CUDA Programming Model

- Fits the scalable nature of the architecture.
- Programmer writes a “Kernel”
 - SPMD (Single Program Multiple Data) style of programming
 - Is executed on the GPU by a hierarchy of threads
 - Threads
 - Warps
 - Blocks
 - Grid



Blocks of threads



CUDA Example

CUDA Example: Dot Product

Sequential C code

```
float dotProduct(float *x, float *y, unsigned int n) {  
    float r = 0.0f;  
    for (int i = 0; i < n; ++i) {  
        r += x[i] * y[i];  
    }  
    return r;  
}
```

- Not what you want to do on a GPU

CUDA dotProduct

- Split computation into a multiplication phase and a summing phase.
 - Both end up being parallelizable.

CUDA dotProduct: elementwise multiplication

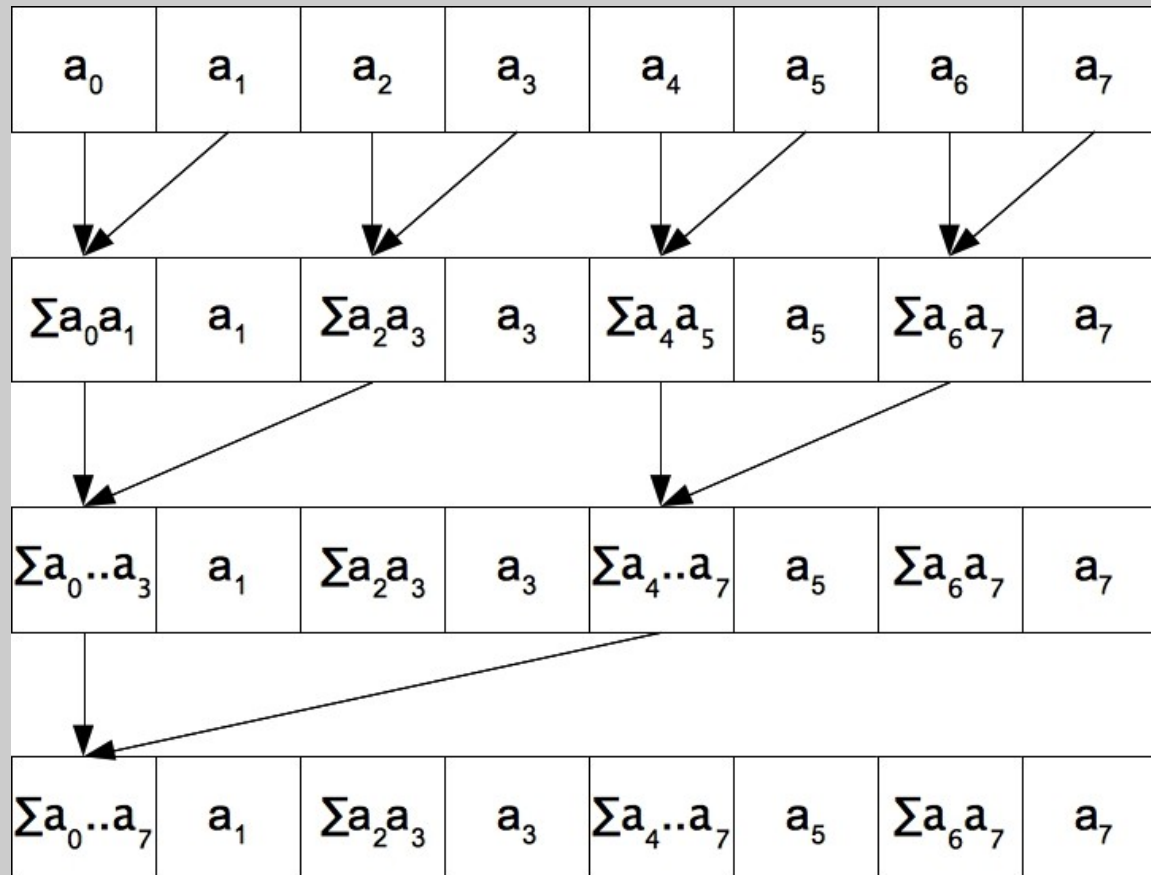
CUDA Code

```
__global__ void multKernel(float *result, float *x, float *y){  
    unsigned int gtid = blockIdx.x * blockDim.x + threadIdx.x;  
    result[gtid] = x[gtid] * y[gtid];  
}
```

- `threadIdx`: identifies a thread within a block (a vector of 3 integers)
- `blockIdx`: identifies a block within a grid (a vector of 2 integers)
- `blockDim`: specifies the extents of the blocks (a vector of 3 integers)
- `__global__`: specifies that this function is a CUDA kernel.

CUDA dotProduct: summation

- Sum up the products.



CUDA dotProduct: summation

CUDA Code

```
__global__ void sumKernel(float *result, float *x){  
    unsigned int tid = threadIdx.x;  
  
    extern __shared__ float sm[];  
  
    sm[tid] = x[blockIdx.x * blockDim + tid];  
  
    for (int i = 1; i < blockDim.x; i *=2) {  
        __syncthreads();  
        if (tid % (2*i) == 0) {  
            sm[tid] += sm[tid + i];  
        }  
    }  
    if (tid == 0) {  
        result[blockIdx.x] = sm[0];  
    }  
}
```

- Sums up an array “that fits in a block”
- Uses shared memory
- Uses __syncthreads()

CUDA dotProduct

- We have:
 - A CUDA kernel that can multiply two arrays (of “any” size) element-wise.
 - A CUDA kernel that can sum up arrays
 - 32, 64, 128, 256, ... 1024 elements for example.

CUDA dotProduct

- Launching Kernels on the GPU

CUDA Host Code

```
multKernel<<<128, 512, 0>>>(device_x, device_x, device_y);  
sumKernel<<<128, 512, 512*sizeof(float)>>>(result, device_x);  
sumKernel<<<1, 128, 128*sizeof(float)>>>(result, result);
```

- Computes the dotProduct of two (128 * 512)-element arrays.
- device_x, device_y and result arrays in “device memory”

CUDA dotProduct: potential optimizations

- Create a fused “mult-sum” kernel

```
multSumKernel<<<128, 512, 0>>>(result, device_x, device_y);  
sumKernel<<<1, 128, 128*sizeof(float)>>>(result, result);
```

- Compute more “results” per thread
 - Use fewer threads in total.
 - Better utilize memory bandwidth.
- Unroll loops, specialize kernel to a particular block-size.
 - Many few-threaded blocks, few many-threaded blocks?
- Changes like these means:
 - Rethink indexing computations.
 - Much rewriting of your kernels.

CUDA

- CUDA is a huge improvement.
- CUDA C is not C.
- Kernels are not easily composed.
- “tweaking” kernels is cumbersome.

Obsidian

Obsidian

- A language for GPU kernel implementation.
 - Embedded in Haskell.
- Goals
 - Compose kernels easily
 - Raise the level of abstraction while maintaining control.
 - Use combinators (higher order functions).
 - Building blocks view on kernel implementation.
 - Think in “data-flow” and “connection-patterns” instead of indexing
 - Generate CUDA code

Obsidian: Small Example

- Increment every element in an array

```
incrAll :: Num a => Arr a :-> Arr a  
incrAll = pure$ fmap (+1)
```

- Can be executed on the GPU

```
*Main> execute incrAll [0..9 :: IntE]  
[1,2,3,4,5,6,7,8,9,10]
```

Obsidian: Small Example

- Or look at the generated CUDA.

```
*Main> execute incrAll [0..9 :: IntE]  
[1,2,3,4,5,6,7,8,9,10]
```

```
genKernel "incrKern" incrAll (mkArr undefined 10 :: Arr IntE)
```

Generated CUDA

```
__global__ void incrKern(word* input0,word* result0){  
  unsigned int tid = (unsigned int)threadIdx.x;  
  ix_int(result0,(tid + (10 * blockIdx.x))) =  
    (ix_int(input0,(tid + (10 * blockIdx.x))) + 1);  
}
```

Obsidian: Small Example

The details

Kernel

```
incrAll :: Num a => Arr a :-> Arr a  
incrAll = pure$ fmap (+1)
```

$\text{fmap } (+1) :: \text{Arr } a \rightarrow \text{Arr } a$

$\text{pure} :: (a \rightarrow b) \rightarrow a \rightarrow b$

Obsidian: Small Example

The details

- Arrays (Arr a)

```
data Arr a = Arr (IndexE -> a) Int
```

- Describes how to compute an element given an index.

```
rev :: Arr a -> Arr a
rev arr = mkArr ixf n
  where
    ixf ix = arr ! (fromIntegral (n-1) - ix)
    n = len arr
```

```
fmap f arr = mkArr (\ix -> f (arr ! ix)) (len arr)
```

Obsidian: Small Example

The details

AST

```
*Main> execute incrAll [0..9 :: IntE]  
[1,2,3,4,5,6,7,8,9,10]
```

AST

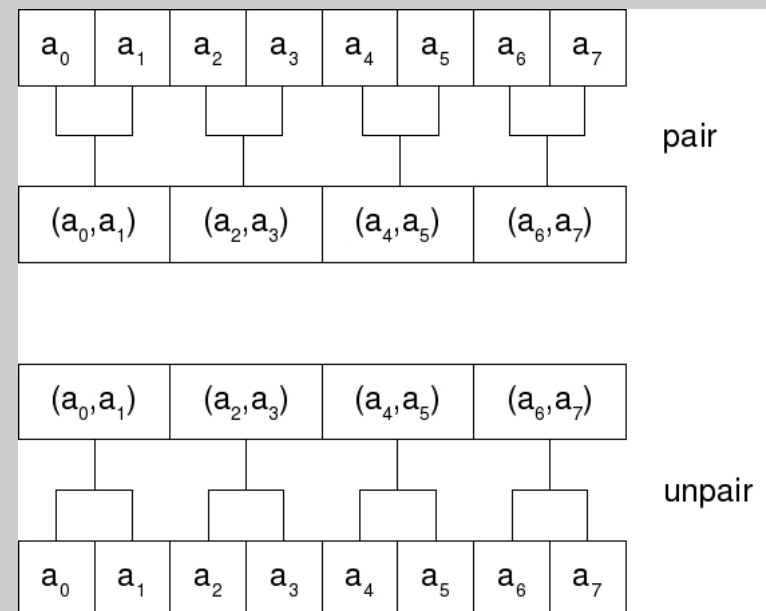
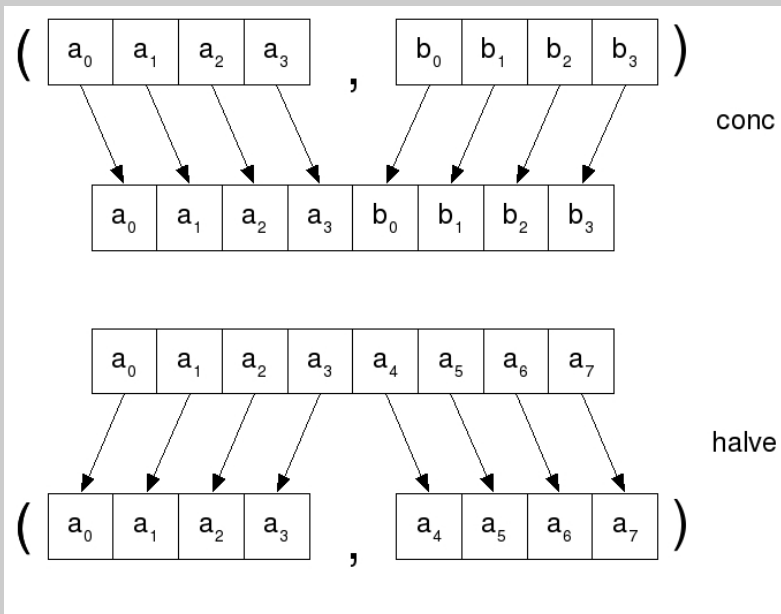
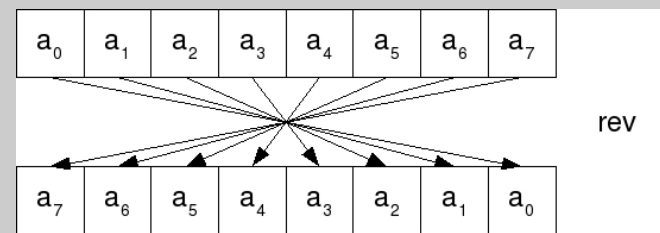
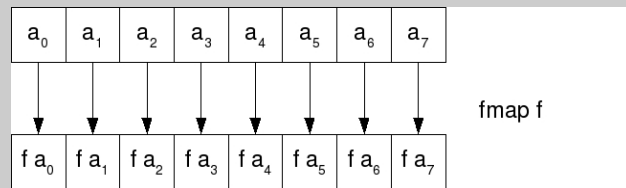
```
genKernel "incrKern" incrAll (mkArr undefined 10 :: Arr IntE)
```

?

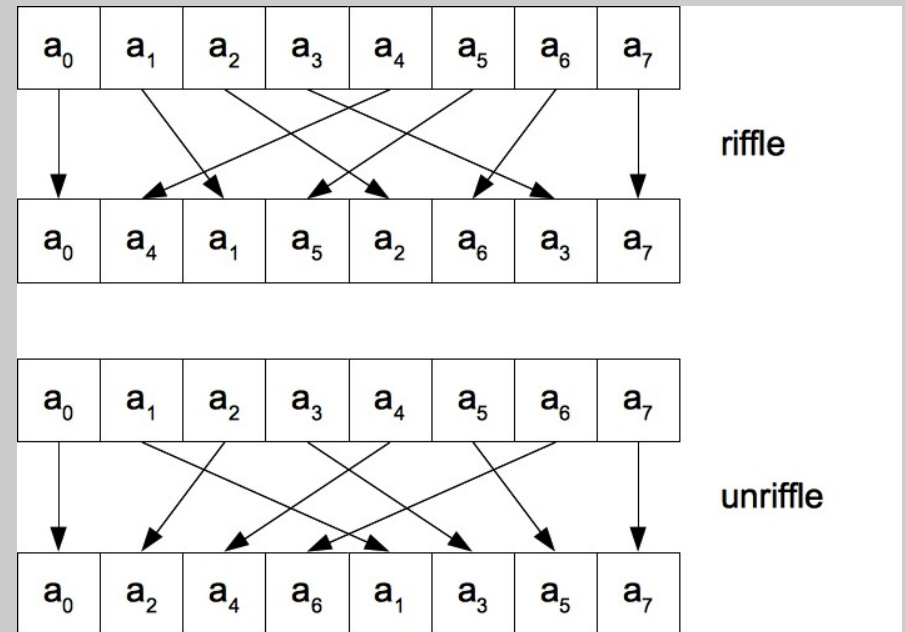
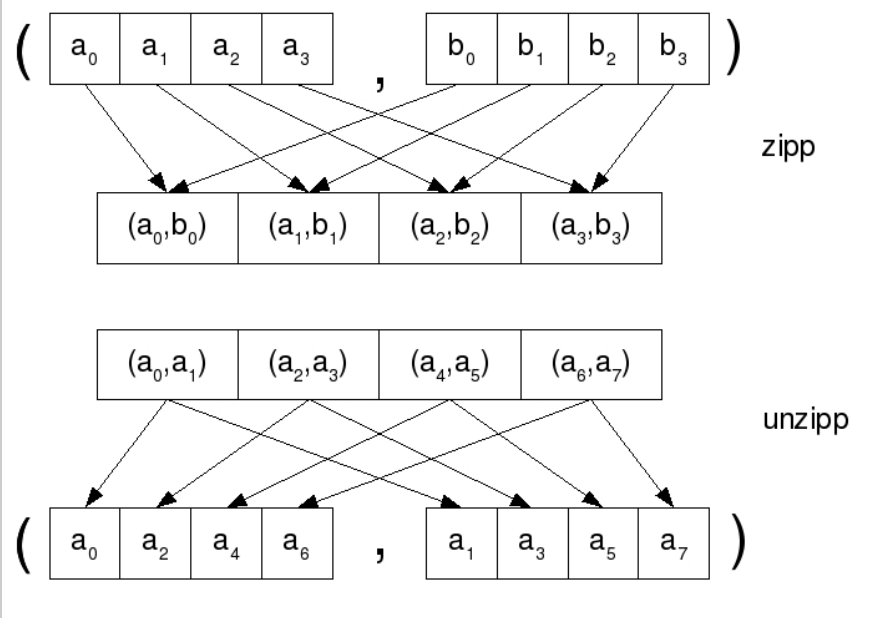
```
data DExp  
  = LitInt Int  
  | LitUInt Word32  
  | LitBool Bool  
  | LitFloat Float  
  | Op2 Op2 DExp DExp  
  | Op1 Op1 DExp  
  | If DExp DExp DExp  
  ...
```

```
type Exp a = E DExp  
type IntE  = Exp Int
```

Building Blocks



Building Blocks



Obsidian:

Expanding the small example

```
incrRev0 :: Num a => Arr a :-> Arr a  
incrRev0 = incrAll ->- pure rev
```

- Sequential composition of Kernels.

```
*Main> execute incrRev0 [0..9 :: IntE]  
[10,9,8,7,6,5,4,3,2,1]
```

Obsidian:

Expanding the small example

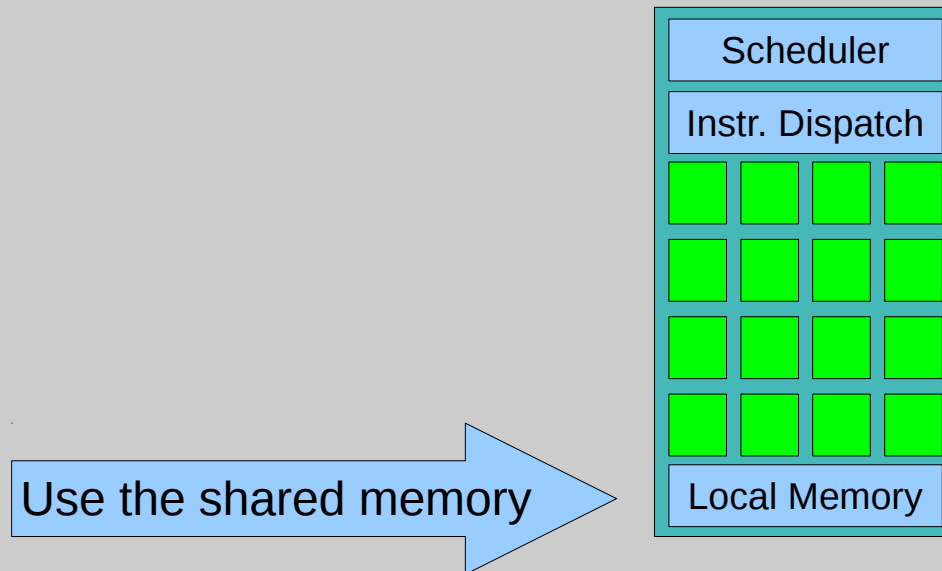
```
incrRev1 :: Num a => Arr a :-> Arr a  
incrRev1 = pure$ rev . fmap (+1)
```

- Could have used Haskell function composition for same result.

```
*Main> execute incrRev1 [0..9 :: IntE]  
[10,9,8,7,6,5,4,3,2,1]
```

Obsidian:

Expanding the small example



```
incrRev2 :: (Flatten a, Num a) => Arr a :-> Arr a
incrRev2 = incrAll ->- sync ->- pure rev
```

- Store intermediate result in shared memory.

```
*Main> execute incrRev2 [0..9 :: IntE]
[10,9,8,7,6,5,4,3,2,1]
```

The generated code

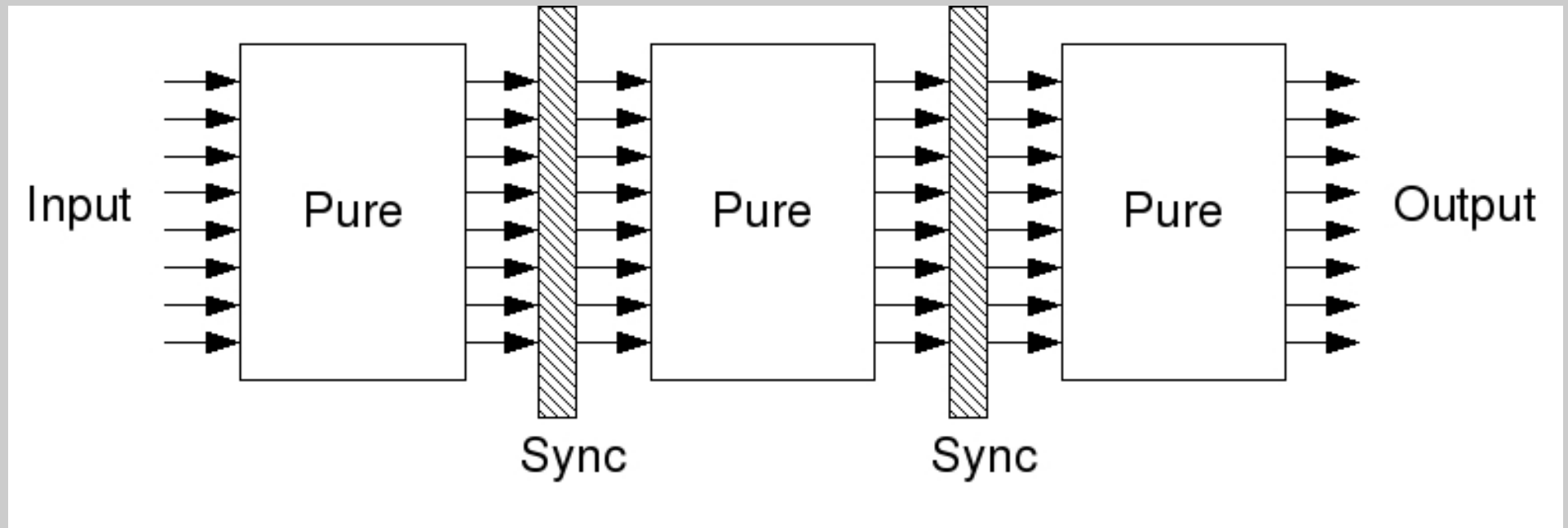
```
__global__ void incrRev1(word* input0,word* result0){  
  unsigned int tid = (unsigned int)threadIdx.x;  
  ix_int(result0,(tid + (10 * blockIdx.x))) =  
    (ix_int(input0,((9 - tid) + (10 * blockIdx.x))) + 1);  
}
```

```
__global__ void incrRev2(word* input0,word* result0){  
  unsigned int tid = (unsigned int)threadIdx.x;  
  extern __shared__ unsigned int s_data[];  
  word __attribute__((unused)) *sm1 = &s_data[0];  
  word __attribute__((unused)) *sm2 = &s_data[10];  
  ix_int(sm1,tid) =  
    (ix_int(input0,(tid + (10 * blockIdx.x))) + 1);  
  __syncthreads();  
  ix_int(result0,(tid + (10 * blockIdx.x))) =  
    ix_int(sm1,(9 - tid));  
}
```

Seen so far

- Create kernels.
pure
- Sequential composition of kernels.
->-
- Store intermediate results in shared memory or “fuse” computations.
sync
- Combinators and permutations.
fmap and rev
- Length of array specifies degree of parallelism

Obsidian Kernels



```
data a :-> b where
  Pure  :: (a -> b) -> (a :-> b)
  Sync  :: (a -> Arr FData) -> (Arr FData :-> b) -> (a :-> b)
```

Obsidian: dotProduct

- Same approach as in the CUDA example
 - A multKernel and one sumKernel

```
multKern :: (Arr FloatE, Arr FloatE) :-> Arr FloatE  
multKern = pure$ zipWith (*)
```

Obsidian: dotProduct

- Implement a similar binary tree shaped summation as in the CUDA example.

```
reduce :: Flatten a => Int -> (a -> a -> a) -> Arr a :-> Arr a
reduce 0 f = pure id
reduce n f = pure op ->- sync ->- reduce (n-1) f
  where
    op = fmap (uncurry f) . pair
```

- Sync is used to obtain parallelism.

Obsidian: dotProduct

```
dotProduct :: Int -> (Arr FloatE, Arr FloatE) -> Arr FloatE  
dotProduct n = multKern ->- sync ->- reduce n (+)
```

Obsidian: dotProduct

Generated Code

```
__global__ void dotProduct(word* input0, word* input1, word* result0){
    unsigned int tid = (unsigned int)threadIdx.x;
    extern __shared__ unsigned int s_data[];
    word __attribute__((unused)) *sm1 = &s_data[0];
    word __attribute__((unused)) *sm2 = &s_data[8];
    ix_float(sm1, tid) = (ix_float(input0, (tid + (8 * blockIdx.x))) *
                          ix_float(input1, (tid + (8 * blockIdx.x))));

    __syncthreads();
    if (tid < 4){
        ix_float(sm2, tid) = (ix_float(sm1, (tid << 1)) +
                              ix_float(sm1, ((tid << 1) + 1)));
    }
    __syncthreads();
    if (tid < 2){
        ix_float(sm1, tid) = (ix_float(sm2, (tid << 1)) +
                              ix_float(sm2, ((tid << 1) + 1)));
    }
    __syncthreads();
    if (tid < 1){
        ix_float(sm2, tid) = (ix_float(sm1, (tid << 1)) +
                              ix_float(sm1, ((tid << 1) + 1)));
    }
    __syncthreads();
    if (tid < 1){
        ix_float(result0, (tid + blockIdx.x)) = ix_float(sm2, tid);
    }
}
```

Obsidian

CUDA dotProduct: potential optimizations

- Create a fused “mult-sum” kernel

Easy

```
multSumKernel<<<128, 512, 0>>>(result, device_x, device_y);  
sumKernel<<<1, 128, 128*sizeof(float)>>>(result, result);
```

- Compute more “results” per thread

Not as easy as we like

- Use fewer threads in total.
- Better utilize memory bandwidth.

- Unroll loops, specialize kernel to a particular block-size

Ok

- Many few-threaded blocks, few many-threaded blocks?

The reversed is hard

- Changes like these means:

- Rethinking indexing computations.
- Much rewriting of your kernels.

Case Studies

Case Studies

- Reduction
- Dot product
- Mergers
- Sorters
- Parallel prefix

Case Studies:

dotProduct

```
dotProduct0 :: Int -> (Arr FloatE, Arr FloatE) -> Arr FloatE
dotProduct0 n = multKern ->- sync ->- reduce n (+)
```

```
dotProduct1 :: Int -> (Arr FloatE, Arr FloatE) -> Arr FloatE
dotProduct1 n = multKern ->- reduce n (+)
```

Kernel	Threads per block	Elms. per block	ms per block
dotProduct0	256	2*256	0.0015
dotProduct1	128	2*256	0.0013
CUDA	256	2*256	0.0030

Case Studies:

Parallel prefix

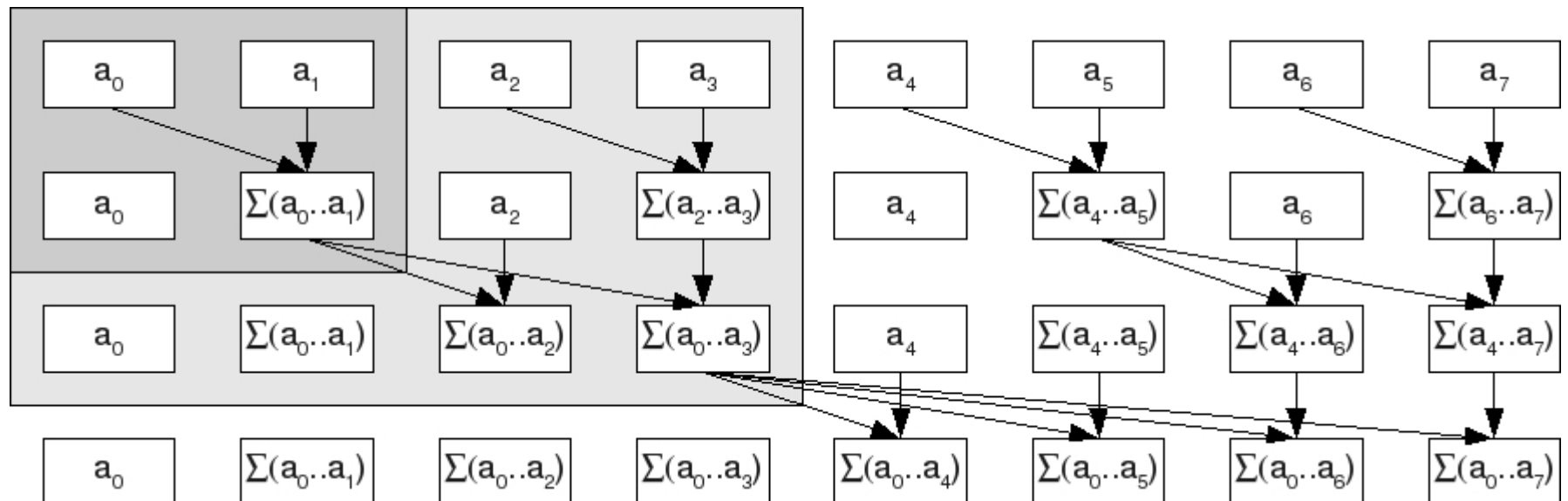
- Given an associative binary operator, $\oplus$, and an array s , compute:

```
r[0] = s[0]
r[1] = s[0]  $\oplus$  s[1]
r[2] = s[0]  $\oplus$  s[1]  $\oplus$  s[2]
...
r[n] = s[0]  $\oplus$  ...  $\oplus$  s[n]
```

- A building block in many parallel algorithms
 - Stream compaction
 - Sorting
 - Many examples in: Prefix Sums and Their Applications - Guy E. Blelloch

Case Studies:

Parallel prefix



Case Studies:

Parallel prefix

```
sklansky :: (Flatten a, Choice a) =>
           Int -> (a -> a -> a) -> (Arr a :-> Arr a)
sklansky 0 op = pure id
sklansky n op = two (sklansky (n-1) op) ->- pure (fan op)
               ->- sync

fan op arr = conc (a1, (fmap (op c) a2))
  where (a1,a2) = halve arr
        c       = a1 ! (fromIntegral (len a1 - 1))
```

Kernel	Threads	ms on GTX320M	ms on GTX480
Handcoded no opt.	512	4.36	0.34
Handcoded opt.	256	2.93	0.23
Obsidian Generated	512	3.84	0.32

Obsidian

- Language for implementing kernels
 - No “kernel coordination”
- Kernel composition is easy
 - >- sequentially
 - two special kind of parallel composition
- Kernels use shared memory for intermediate results.

Related Work

- `Data.Array.Accelerate`
 - Higher level language compared to Obsidian.
 - Map, Fold, ZipWith – primitives.
 - Not the same detailed control.
 - Most complete and well developed tool for Haskell based GPU programming today.

Related Work

- Nikola
 - Higher level language compared to Obsidian.
 - Similar to Accelerate in that sense.
 - Effort seems to be in developing methods for EDSL implementation.

Related Work

- Copperhead (Data-parallel python)
 - Compiles a subset of Python into CUDA for GPU execution.
 - Very fresh.

Conclusions and Future work

- Obsidian strong sides.
 - Elegant descriptions of kernels.
 - Compositional kernels.
- Kernel Coordination is needed.
 - Depending on path of GPU evolution.
- Kernel Performance can be improved.
 - Hard to compare performance to that of related work.

Extra Generated Code

```

__global__ void sklansky128(word* input0, word* result0){
    unsigned int tid = (unsigned int)threadIdx.x;
    extern __shared__ unsigned int s_data[];
    word __attribute__((unused)) *sm1 = &s_data[0];
    word __attribute__((unused)) *sm2 = &s_data[128];
    ix_int(sm1, tid) = (((tid & 0xffffffff81) < 1) ?
        ix_int(input0, (tid + (128 * blockIdx.x))) :
        (ix_int(input0, ((tid & 0x7e) + (128 * blockIdx.x))) +
        ix_int(input0, (tid + (128 * blockIdx.x)))));
    __syncthreads();
    ix_int(sm2, tid) = (((tid & 0xffffffff83) < 2) ?
        ix_int(sm1, tid) :
        (ix_int(sm1, ((tid & 0x7c) | 0x1)) + ix_int(sm1, tid)));
    __syncthreads();
    ix_int(sm1, tid) = (((tid & 0xffffffff87) < 4) ?
    ix_int(sm2, tid) :
    (ix_int(sm2, ((tid & 0x78) | 0x3)) + ix_int(sm2, tid)));
    __syncthreads();
    ix_int(sm2, tid) = (((tid & 0xffffffff8f) < 8) ?
    ix_int(sm1, tid) :
    (ix_int(sm1, ((tid & 0x70) | 0x7)) + ix_int(sm1, tid)));
    __syncthreads();
    ix_int(sm1, tid) = (((tid & 0xffffffff9f) < 16) ?
    ix_int(sm2, tid) :
    (ix_int(sm2, ((tid & 0x60) | 0xf)) + ix_int(sm2, tid)));
    __syncthreads();
    ix_int(sm2, tid) = (((tid & 0xffffffffbf) < 32) ?
    ix_int(sm1, tid) :
    (ix_int(sm1, ((tid & 0x40) | 0x1f)) + ix_int(sm1, tid)));
    __syncthreads();
    ix_int(sm1, tid) = ((tid < 64) ?
    ix_int(sm2, tid) :
    (ix_int(sm2, 63) + ix_int(sm2, tid)));
    __syncthreads();
    ix_int(result0, (tid + (128 * blockIdx.x))) = ix_int(sm1, tid);
}

```