## AMS 148 Lecture 5

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Baskin
Engineering
USANTHAGRUL

## Overview

(1) Reduce

- Parallel Add Reduce
- Brent's Theorem
- CUDA Reduce
- Finite Integrals using Reduce
(2) Scan
- Inclusive Scan
- Exclusive Scan
- Application to CDF calculation

How do we add one billion floats $\in[1,2)$

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```
summ = 0.0f;
for(int i = 0; i < n; i++)
    summ += array[i];
```


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- How can we solve these issues?


## Reduce

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- Reduces an array to one data point
- Requires a binary associative operator.


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- The reduce is cast as

$$
\mathcal{R}(\mathbf{x}, \oplus)=x_{0} \oplus x_{1} \oplus \cdots \oplus x_{n-1}
$$

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    summ += array[i];
```

How can we use the above assumptions to make this summation parallel?

## Computational Tree



## Parallel Sum Computational Tree

On the Board

## Complexity of Parallel Reduce

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| :--- | :--- |
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| 8 | 3 |

Table: Step complexity for parallel reduce

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$$
\text { Steps }=\mathcal{O}\left(\log _{2}(N)\right)
$$

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Note it only scales like $\log _{2}(N)$ if we have $N$ processors. Suppose we have only $p<N$ processors?

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Note it only scales like $\log _{2}(N)$ if we have $N$ processors. Suppose we have only $p<N$ processors? Then we use Brent's Theorem, to find the true scaling.

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- These trees are often directed acyclic graphs(DAGs)
- DAGs are useful to illustrate an algorithms flow and dependencies



## Example DAGs



Figure: Example directed acyclic graph

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Then Brent's Theorem states:

$$
\frac{T_{1}}{p} \leq T_{P} \leq \frac{T_{1}}{p}+T_{\infty}
$$

So for a reduce algorithm

$$
T_{p} \leq \frac{T_{1}}{p}+T_{\infty}=\frac{N}{p}+\log _{2}(N)
$$

## Parallel Summation

Lets sum a million points (acutally $2^{20}$ ).

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```
float Bad_serial_reduce(const float *data, int N)
{
```

```
float summ =0.0f;
```

float summ =0.0f;
for(int i = 0; i < N; i++)
for(int i = 0; i < N; i++)
summ+= data[i];
summ+= data[i];
return summ;

```
return summ;
```

- this is bad
- we'll do two different ways in CUDA


## Application Of Reduce

It is known that

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\int_{-1}^{1} \sqrt{1-x^{2}} d x=\frac{\pi}{2}
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- We can calculate more digits of pi this way
- We can test our reduction algorithm with this
- How do we go from an integral to a sum?


## Numerical Integration

Composite Trapezoidal Rule:

$$
\int_{a}^{b} f(x) d x \approx \sum_{1}^{N}\left(f\left(x_{j-1}\right)+f\left(x_{j}\right)\right) \frac{\delta x}{2}
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where

$$
[a, b]=\bigcup_{i=1}^{N}\left[x_{i-1}, x_{i}\right]
$$

and $a=x_{0}$, and $b=x_{N}$.

## Kernels

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In our application we will set $N=2^{20}$.

- This application is a map-reduce algorithm
- We must Map onto $f(x)=\sqrt{1-x^{2}}$
- Then we have two stages of reduce.
- Lastly we will multiply the result by 2 .


## Scan

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- Scan is a generalization of reduce to yield an array
- Any binary operation can be used in a scan algorithm
- Notable applications: CDF calculation, sorting algorithms


## A Short Example

> Input: $\{1,2,3,4\}$
> Operation: +
> Output: $\{1,3,6,10\}$

## Mathematical Representation of Scan

$$
\mathcal{S}(\mathbf{x}, \oplus)=\mathbf{y}
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- The operator $\oplus$ forms a group over the set of elements in $\mathbf{x}$
- $\oplus$ is associative
- $\oplus$ is closed, i.e. $x \oplus y=z$ where $x, y, z$ are of the same type
- There exists an identity element $e$, that is $e \oplus x=x$ for every element of type $x$


## What does scan do?

Let $\mathcal{S}$ be the scan primitive, and $\oplus$ be a binary operator for the data type, then for an inclusive scan

$$
\begin{gathered}
{\left[a_{0}, a_{1}, a_{2}, \cdots, a_{n-1}\right]: \text { input }} \\
{\left[a_{0}, a_{0} \oplus a_{1}, a_{0} \oplus a_{1} \oplus a_{2}, \cdots, \bigoplus_{j=0}^{n-1} a_{j}\right]: \text { output }}
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$$
\left[a_{0}, a_{1}, a_{2}, \cdots, a_{n-1}\right] \text { :input }
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$$
\left[e, a_{0}, a_{0} \oplus a_{1}, a_{0} \oplus a_{1} \oplus a_{2}, \cdots, \bigoplus_{j=0}^{n-2} a_{j}\right] \text { :output }
$$

## Implementation of scan

```
int acc \(=\) identity; //for op + identity \(=0.0\);
for (int \(=0 ; i<e l e m e n t s . l e n g t h() ; i++\) )
    \{
        acc \(=\) acc op element[i] // acc + element[i]
        or max (acc, element);
    out[i] = acc;
    \}
```


## Hillis and Steele

- Danny Hillis And Guy Steele 1986


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- It's best to observe the graph of this algorithm

Inclusive Scan

## Hillis And Steele Scan



## Properties of the Hillis and Steele Algorithm

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## Properties of the Hillis and Steele Algorithm

- Has Step complexity $\mathcal{O}(\log (n))$
- However has $\mathcal{O}(n \log (n))$ work complexity
- Essentially doing $n$ reductions
- Is an inclusive scan
- Best for small arrays where the number of processors is equal to or greater than the number of array elements.


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## A more work efficient scan?

- Serial scan has a work complexity of $n$
- The Hillis and Steele algorithm is more work complex than serial
- If the number of size of the data array is larger than the number of threads, we seek a more work efficient algorithm than H\&S
- To this effect we look to the Blelloch Scan


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- Requires the downseep "operator"



## Reduce Phase



## Downseep Phase



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- So the Blelloch scan has $2 \log (n)$ steps, but $\mathcal{O}(n)$ work
- Note that the Blelloch Scan is exclusive


## Mix and match

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- Exclusive to Inclusive:
- Shift all elements to the left, drop first element
- Perform operation on last element of scan and last of original array
- Or - store the reduced element in a temporary variable at the end of the ruduce phase


## CDF

- To illustrate the use of scan we will compute a Cummulative Distribution Function


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- To illustrate the use of scan we will compute a Cummulative Distribution Function
- Our underlying Probability Density Function will be the normal distribution.

$$
f\left(x \mid \mu, \sigma^{2}\right)=\frac{1}{\sqrt{2 \pi \sigma^{2}}} \exp \left[\frac{-(x-\mu)^{2}}{2 \sigma^{2}}\right]
$$

The CDF for the Normal distribution is

$$
\Phi\left(x \mid \mu, \sigma^{2}\right)=\frac{1}{2}\left[1+\operatorname{erf}\left(\frac{x-\mu}{\sqrt{2} \sigma}\right)\right]
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- Cannot describe the error function as a combination of elementary functions
- Must find it numerically.


## Definition of CDF

Note that

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- Computers can't do infinity
- However, $f$ is rapidly descreasing
- That is, $f \rightarrow 0$ as $|x| \rightarrow \infty$ "faster" than any polynomial
- And by the empirical rule, $99.7 \%$ of the probability is contained within 3 standard deviations from the mean

$$
\Phi\left(x \mid \mu, \sigma^{2}\right) \approx \int_{x-5 \mu}^{x} f\left(x^{\prime} \mid \mu, \sigma^{2}\right) d x^{\prime}
$$

## Numerical Plan

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(2) Use a Stencil + Map to generate array to be scanned
(3) Use device function to apply normal distribution to $x$
(9) Use work efficient Blelloch Scan to perform the numerical integration
(5) Perform the shift to turn exclusive scan to inclusive

## Stencil + Map Kernel

## Blelloch Scan Kernel

## Shift Kernel

## Generalizing Scan to Larger Arrays

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(9) Use newly updated second array to correct original scan by thread block

