GStream: A General-Purpose Data Streaming Framework on GPU Clusters

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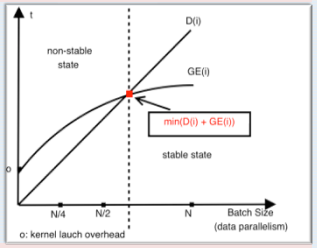
Motivation

➢ GPU's viability to operate on general streaming data is still unknown.
➢ Data streaming processing and data-parallelism are sometimes conflicting
— Streaming processing favors smaller response time – less
— Massive data-parallelism tends to increase response time
— Existing streaming abstraction fails to consider this trade-off

• Suppose input tuples arrive at a steady speed of N/T
• GE(i): GPU execution time for batch size i
• D(i): Response time for batch size i

The larger the batch size, the worse the average and maximum response time



➢ GPU cluster
— Handle different layers of memory

Design Goal

➢ Scalability
— No restriction on the size of the GPU cluster
➢ Transparency
— Task scheduling and GPU/host memory management handled by run-time .
➢ Extendability
— Easy to extend to customized need
➢ Programmability
— Syntax should be concise and provide compile time type-checking
➢ Flexibility
— Easy to switch b/w CPU and GPU execution
— Allows fast prototyping and debugging on CPU
➢ Reusability
— GPU kernels more expensive to develop
— Reusing existing CUDA libraries a plus

Gstream: System Model

➢ Filter
— Encapsulate data processing; consume and/or produce data
— Main body of a filter execution is generalized into three-step pattern:

```
void Filter::run() {
   start();
   while (!isDone())
      kernel();
   finish();
}
```

➢ Channel
— One-way Links b/w filters
— Two types of channels:
— p2p channel: links a predecessor and a successor filter
— group channel: links array of filters, well-defined communication pattern (broadcast, reduce, all-to-all etc.)
➢ Operator "|" to concatenate filters using channel
— Concise, yet powerful to express complicated filter mapping

Gstream APIs

StreamSystem APIs:

void addFilter(FilterBase *filter)
void run();

Filter Functions to be Overridden:

void kernel()* (GPU kernels are launched inside)
void start()+ (empty by default)
void finish()+ (empty by default)
int getMinDegree(int portId)
int getMaxDegree(int portId)
*: must overridden; +: has default behavior

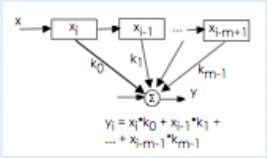
Channel Push APIs:

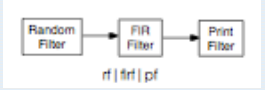
void reserve (StreamChannelBuffer &buffer, int size)
void reserve_finalize (int size)

Channel Pop APIs:

void pop (StreamChannelBuffer &buffer, int min, int max)
void pop_finalize (int size)

Case Study: Finite Impulse Response Filter

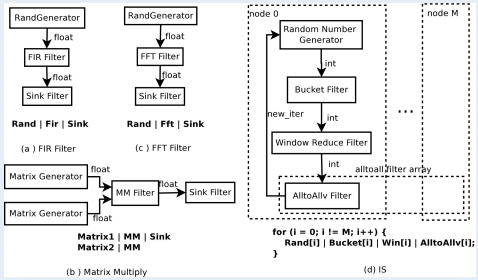





```
int main() {
    StreamSystem ss;
    RandomFilter<float>rf;
    FirFilter<float, 100> firf; // a FIR
filter with degree m = 100
    OutputFilter<float> pf;

    /* add filters to system */
    ss.addFilter(&rf);
    ss.addFilter(&firf);
    ss.addFilter(&pf);

    /* construct the channel*/
    rf | firf | pf;

    /* ready to run */
    ss.run();
    return 0;
}
```

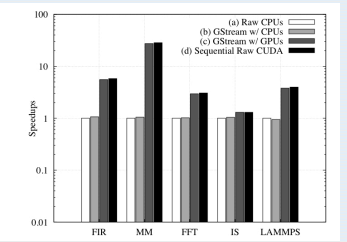
```
template<class T, int m>
class FifFilter: public Filter<typelist1<T>,
typelist1<T> > {
public:
virtual void start() {
    … /* setup coefficients array k[m] */
}
virtual int getMinDegreee(int portId) {
    return m;
}
virtual void kernel(){
    StreamChannelBuffer<T> input;
    StreamChannelBuffer<T> output;
    int batch = inputPort[0]->pop(&input,
getMinDegree(0), getMaxDegree(0));
    if (batch != -1) {
        outputPort[0]->reserve(&output, batch –m
+ 1);
        … /* computation, omitted */
        /* output ready, finalize the reserve*/
        outputPort[0]->reserve_finalize();
        /* input port only consumes batch –m +1
        inputPort[0]->pop_finalize(batch-m+1);
    } else {  /* terminate condition */
        setDone();
    }
Private:
    float k[m];
}
};
```

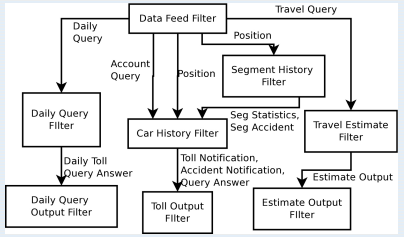
Experimental Results



➢ FIR: degree 100
➢ Matrix Multiply: matrix size 512 X 512
➢ FFT: 2D 512 X 512
➢ Integer Sort (IS)
➢ LAMMPS benchmark

➢ All running on a GPU cluster with 16 nodes
➢ Speedups up to 30X over CPU cluster with the same # of nodes





➢ Linear Road Benchmark: Original designed to provide scalable and fair benchmark for Stream Data Management Systems (SDMS)
➢ Performance measured by L-rating (# of express ways supported w/o breaking response time constraint)
➢ GStream achieve L= 40, in contrast to L=2.5 in Aurora and SPC

Conclusion and Future Work

➢ GStream is a general-purpose, scalable data streaming framework designed for GPU clusters
➢ We present a novel and concise, yet powerful streaming abstraction amenable to GPUs
➢ Gstream is easy to use, applicable to a variety of domains not constrained to traditional streaming problems
➢ Our future work includes:
➢ Expand GStream to NAS benchmarks, making GPU cluster an attractive platform for high-performance computing