Scalable Parallel Primitives for Massive Graph Computation

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Sources of Massive Graphs

Graphs naturally arise from the internet and social interactions.

Many scientific (biological, chemical, cosmological, ecological, etc) datasets are modeled as graphs.

(WWW snapshot, courtesy Y. Hyun)

(Yeast protein interaction network, courtesy H. Jeong)
Types of Graph Computations

Examples:
- Centrality
- Shortest paths
- Network flows
- Strongly Connected Components

Tool: Graph Traversal

Examples:
- Fuzzy intersection
- Clustering, Algebraic Multigrid

Tool: Map/Reduce

Examples:
- Loop and multi edge removal
- Triangle/Rectangle enumeration
Tightly Coupled Computations on Sparse Graphs

- Many graph mining algorithms are computationally intensive. (e.g. graph clustering, centrality)
- Some computations are inherently latency-bound. (e.g. finding shortest paths)
- Interesting graphs are sparse, typically $|\text{edges}| = O(|\text{vertices}|)$

Huge Graphs + Expensive Kernels $\rightarrow$ High Performance and Massive Parallelism

Sparse Graphs/Data $\rightarrow$ Sparse Data Structures (Matrices)
“...my main conclusion after spending ten years of my life on the TeX project is that software is hard. It's harder than anything else I've ever had to do”
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Dealing with software is hard!
Software for Graph Computation

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High performance computing (HPC) software is harder!
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High performance computing (HPC) software is harder!

Deal with parallel HPC software?
Outline

• **The Case for Primitives**
• The Case for Sparse Matrices
• Parallel Sparse Matrix-Matrix Multiplication
• Software Design of the Combinatorial BLAS
• An Application in Social Network Analysis
• Other Work
• Future Directions
All-Pairs Shortest Paths

- **Input:** Directed graph with “costs” on edges
- Find least-cost paths between all reachable vertex pairs
- Classical algorithm: Floyd-Warshall

\[
\text{for } k=1:n \quad // \text{the induction sequence} \\
\text{for } i = 1:n \\
\quad \text{for } j = 1:n \\
\quad \quad \text{if}(w(i \rightarrow k) + w(k \rightarrow j) < w(i \rightarrow j)) \\
\quad \quad \quad w(i \rightarrow j) := w(i \rightarrow k) + w(k \rightarrow j)
\]

- Case study of implementation on multicore architecture:
  - graphics processing unit (GPU)
GPU characteristics

Powerful: two Nvidia 8800s > 1 TFLOPS
Inexpensive: $500 each

But:

• Difficult programming model:
  One instruction stream drives 8 arithmetic units
• Performance is counterintuitive and fragile:
  Memory access pattern has subtle effects on cost
• Extremely easy to underutilize the device:
  Doing it wrong easily costs 100x in time
Based on R-Kleene algorithm

Well suited for GPU architecture:

- Fast matrix-multiply kernel
- In-place computation \(\Rightarrow\) low memory bandwidth
- Few, large MatMul calls \(\Rightarrow\) low GPU dispatch overhead
- Recursion stack on host CPU, not on multicore GPU
- Careful tuning of GPU code

\[ A = A^*; \quad % \text{recursive call} \]
\[ B = AB; \quad C = CA; \]
\[ D = D + CB; \]
\[ D = D^*; \quad % \text{recursive call} \]
\[ B = BD; \quad C = DC; \]
\[ A = A + BC; \]

+ is “min”, \times is “add”
Conclusions:

High performance is achievable but not simple

Carefully chosen and optimized primitives will be key

Lifting Floyd-Warshall to GPU

Unorthodox R-Kleene algorithm

The right primitive!
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• Every graph is a sparse matrix and vice-versa
• Adjacency matrix: sparse array w/ nonzeros for graph edges
• Storage-efficient implementation from sparse data structures
The Case for Sparse Matrices

• Many irregular applications contain sufficient coarse-grained parallelism that can ONLY be exploited using abstractions at proper level.

<table>
<thead>
<tr>
<th>Traditional graph computations</th>
<th>Graphs in the language of linear algebra</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data driven. Unpredictable communication.</td>
<td>Fixed communication patterns.</td>
</tr>
<tr>
<td>Irregular and unstructured. Poor locality of reference</td>
<td>Operations on matrix blocks. Exploits memory hierarchy</td>
</tr>
<tr>
<td>Fine grained data accesses. Dominated by latency</td>
<td>Coarse grained parallelism. Bandwidth limited</td>
</tr>
</tbody>
</table>
Linear Algebraic Primitives

Sparse matrix-matrix Multiplication (SpGEMM)

Element-wise operations

Sparse matrix-vector multiplication

Sparse Matrix Indexing

Matrices on semirings, e.g. (·, +), (and, or), (+, min)
Why focus on SpGEMM?

- Graph clustering (Markov, peer pressure)
- Subgraph / submatrix indexing
- Shortest path calculations
- Betweenness centrality
- Graph contraction
- Cycle detection
- Multigrid interpolation & restriction
- Colored intersection searching
- Applying constraints in finite element computations
- Context-free parsing ...
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Two Versions of Sparse GEMM

1D block-column distribution

\[ C_i = C_i + A B_i \]

Checkerboard (2D block) distribution

\[ C_{ij} += A_{ik} B_{kj} \]
In practice, 2D algorithms have the potential to scale, if implemented correctly. Overlapping communication, and maintaining load balance are crucial.
Compressed Sparse Columns (CSC): A Standard Layout

- Stores entries in column-major order
- Dense collection of “sparse columns”
- Uses $O(n + nnz)$ storage.
Submatrices are “hypersparse” (i.e. $\text{nnz} << n$)

$\sqrt{p}$ blocks

Average of $c$ nonzeros per column

Total Storage:

$O(n + \text{nnz}) \Rightarrow O(n\sqrt{p} + \text{nnz})$

- A data structure or algorithm that depends on the matrix dimension $n$ (e.g. CSR or CSC) is asymptotically too wasteful for submatrices
Sequential Hypersparse Kernel

Standard algorithm’s complexity:
\( \Theta(\text{flops} + \text{nnz}(B) + n + m) \)

New hypersparse kernel:
\( \Theta(\text{flops} \cdot \lg ni + \text{nnz}(A) + \text{nnz}(B)) \)

- Strictly \( O(\text{nnz}) \) data structure
- Outer-product formulation
- Work-efficient
Scaling Results for SpGEMM

- RMat X RMat product (graphs with high variance on degrees)
- Random permutations useful for the overall computation.
- Bulk synchronous algorithms may still suffer due to imbalance within the stages.
- Asynchronous algorithm to avoid the curse of synchronicity
- One sided communication via RDMA (using MPI-2)
- Results obtained on TACC/Lonestar for graphs with average degree 8
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**Generality**, of the numeric type of matrix elements, algebraic operation performed, and the library interface.

Without the language abstraction penalty: C++ Templates

```cpp
template <class IT, class NT, class DER>
class SpMat;
```

- Achieve mixed precision arithmetic: Type traits
- Enforcing interface and strong type checking: CRTP
- General semiring operation: Function Objects

- Abstraction penalty is not just a programming language issue.
- In particular, view matrices as indexed data structures and stay away from single element access (Interface should discourage)
**Extendability**, of the library while maintaining compatibility and seamless upgrades.

➡ Decouple parallel logic from the sequential part.

Commonalities:
- Support the sequential API
- Composed of a number of arrays

Any parallel logic: asynchronous, bulk synchronous, etc

SpPar<Comm, SpSeq>
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Social Network Analysis

Applications

- Community Detection
- Network Vulnerability Analysis

Combinatorial Algorithms

- Betweenness Centrality
- Graph Clustering
- Contraction

Parallel Combinatorial BLAS

- SpGEMM
- SpRef/SpAsgn
- SpMV
- SpAdd

Betweenness Centrality (BC)

$C_B(v)$: Among all the shortest paths, what fraction of them pass through the node of interest?

$$C_B(v) = \sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

Brandes’ algorithm
Betweenness Centrality using Sparse GEMM

- Parallel breadth-first search is implemented with sparse matrix-matrix multiplication
- Work efficient algorithm for BC
BC Performance on Distributed-memory

- **TEPS**: Traversed Edges Per Second
- Batch of 512 vertices at each iteration
- Code only a few lines longer than Matlab version

**Input:** RMAT scale N
2\(^N\) vertices
Average degree 8

Pure MPI-1 version.
No reliance on any particular hardware.
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Our parallel algorithms for $y \leftarrow Ax$ and $y' \leftarrow A^T x'$ using the new \textit{compressed sparse blocks (CSB)} layout have

- $\Theta(\sqrt{n \lg n})$ span, and $\Theta(nnz)$ work,
- yielding $\Theta(nnz/\sqrt{n \lg n})$ parallelism.
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Future Directions

- Novel scalable algorithms
- Static graphs are just the beginning. Dynamic graphs, Hypergraphs, Tensors
- Architectures (mainly nodes) are evolving
  - Heterogeneous multicores
  - Homogenous multicores with more cores per node

Hierarchical parallelism

TACC Lonestar (2006) 4 cores / node

TACC Ranger (2008) 16 cores / node

SDSC Triton (2009) 32 cores / node

XYZ Resource (2020)
New Architectural Trends

LANL / IBM Roadrunner

A unified architecture?

Cray XMT

Intel 80-core chip

NVIDIA Tesla
Remarks

- Graph computations are pervasive in sciences and will become more so.
- High performance software libraries improve productivity.
- Carefully chosen and implemented primitive operations are key to performance.
- Linear algebraic primitives:
  - General enough to be widely useful
  - Compact enough to be implemented in a reasonable time.
Related Publications

• Hypersparsity in 2D decomposition, sequential kernel.
  B., Gilbert, "On the Representation and Multiplication of Hypersparse Matrices“, IPDPS’08

• Parallel analysis of sparse GEMM, synchronous implementation
  B., Gilbert, "Challenges and Advances in Parallel Sparse Matrix-Matrix Multiplication, ICPP’08

• The case for primitives, APSP on the GPU

• SpMV on Multicores
  B., Fineman, Frigo, Gilbert, Leiserson, "Parallel Sparse Matrix-Vector and Matrix-Transpose-Vector Multiplication using Compressed Sparse Blocks“, SPAA’09

• Betweenness centrality results
  B., Gilbert, “Parallel Sparse Matrix-Matrix Multiplication and Large Scale Applications”

• Software design of the library
  B., Gilbert, “Parallel Combinatorial BLAS: Interface and Reference Implementation”
Acknowledgments…