

Implementing Scalable Parallel Search Algorithms for Data-Intensive Applications

Ted Ralphs
Industrial and Systems Engineering
Lehigh University
<http://www.lehigh.edu/~tkr2>

Laszlo Ladanyi
IBM T.J. Watson Research Center

Matt Saltzman
Clemson University

Outline of Talk

- Overview of **parallel tree search**
 - Knowledge sharing
 - Data-intensive applications
- Overview of **branch, cut, and price** algorithms
- The **Abstract Library for Parallel Search** (ALPS)
 - Scalability
 - Data handling
- Computational results
- Conclusions

Parallel Systems and Scalability

- Parallel System: Parallel algorithm + parallel architecture.
- Scalability: How well a **parallel system** takes advantage of increased computing resources.
- Terms

Sequential runtime	T_s
Parallel runtime	T_p
Parallel overhead	$T_o = NT_p - T_s$
Speedup	$S = T_s/T_p$
Efficiency	$E = S/N$

Tree Search Algorithms

- Types of **Tree Search Problems**
 - Simple search
 - Complete search
 - Optimal search (DOPs)
- **Application Areas**
 - **Discrete Optimization**
 - Artificial Intelligence
 - Game Playing
 - Theorem Proving
 - Expert Systems
- Elements of **Search Algorithms**
 - **Node splitting** method (branching)
 - **Search order**
 - **Pruning** rule
 - **Bounding** method (optimization only)

Constructing Parallel Tree Search Algorithms

- Main contributors to parallel overhead
 - Communication Overhead
 - Idle Time (Ramp Up/Down Time)
 - Idle Time (Handshaking)
 - Performance of Non-critical Work
- Non-critical work is essentially work that would not have been performed in the sequential algorithm.
- The primary way in which tree search algorithms differ is the way in which *knowledge* is shared.
- Sharing knowledge helps eliminate the performance of **non-critical work**.
- If all processes have “**perfect knowledge**,” then no non-critical work will be performed.
- However, knowledge sharing may also increase communication overhead and idle time.

Knowledge Bases

- Knowledge is shared through *knowledge bases*.
- Methods for disseminating knowledge
 - Pull: Process requests information from the knowledge base (asynchronously or synchronously).
 - Push: Knowledge base broadcasts knowledge to processes.
 - An important parameter to consider is whether the current task is interrupted when knowledge is received or not.
- Basic examples of knowledge to be shared.
 - Bounds
 - Node Descriptions
- We will see more later.

Data-intensive Tree Search

- In some applications, the amount of information needed to describe each search tree node is very large.
- This can make memory an issue and also increase communication overhead.
- Abstractly, we will think of each node as being described by a list of *objects*.
- For the applications we are interested in, the list of objects does not change much from parent to child.
- We can therefore store the description of an entire subtree very compactly using *differencing*.

Example: Combinatorial Optimization

- A *combinatorial optimization problem* $CP = (E, \mathcal{F})$ consists of
 - A *ground set* E ,
 - A set $\mathcal{F} \subseteq 2^E$ of *feasible solutions*, and
 - A *cost function* $c \in \mathbf{Z}^E$ (optional).
- The *cost* of $S \in \mathcal{F}$ is $c(S) = \sum_{e \in S} c_e$.
- Problem: Find a least cost member of \mathcal{F} .
- Example: The Integer Knapsack Problem
 - We have a set of n items with weights w_i and profits p_i .
 - We want to choose the **most profitable subset** of the n items such that the total weight is less than W .
 - We can branch by choosing an item and either forcing it in or out of the knapsack.

Branch and Bound

- *Branch and bound* is the most commonly-used algorithm for solving combinatorial optimization problems.
- It is a *divide and conquer* approach.
- Suppose F is the set of feasible solutions and we wish to solve $\min_{s \in F} c^T x$.
- Consider a *partition* of F into subsets F_1, \dots, F_k . Then

$$\min_{x \in F} c^T x = \min_{\{1 \leq i \leq k\}} \left\{ \min_{x \in F_i} c^T x \right\}$$

- The branch and bound method is to solve each of the new subproblem recursively.
- If we cannot solve a given subproblem, then we try to either derive a bound that will allow us to *prune* it or prove it is *infeasible*.
- Failing that, we further subdivide the problem (*branch*).

Knowledge Sharing in BCP

- In BCP, knowledge discovery consists of finding the **linear inequalities** that describe or approximate the polyhedron.
- The more inequalities we know, the better bounds we can obtain.
- Finding these inequalities can be time consuming, so we want to **share** them when they are found.
- Hence we have a new kind of knowledge that must be shared.
- Knowledge bases in BCP
 - **Node Pools**
 - **Inequality Pools**

The ALPS Project

- In partnership with IBM and the COIN-OR project.
- Multi-layered C++ class library for implementing scalable, parallel tree search algorithms.
- Design is fully generic and portable.
 - Support for implementing general **tree search algorithms**.
 - Support for any **bounding** scheme.
 - **No assumptions** on problem/algorithm type.
 - No dependence on **architecture/operating system**.
 - No dependence on **third-party software** (communications, solvers).
- Emphasis on parallel **scalability**.
- Support for large-scale, **data-intensive** applications (such as BCP).
- Support for **advanced methods** not available in commercial codes.

ALPS Design

Modular library design with minimal assumptions in each layer.

ALPS Abstract Library for Parallel Search

- manages the search tree.
- prioritizes based on **quality**.

BiCePS Branch, Constrain, and Price Software

- manages the data.
- adds notion of **objects** and **differencing**.

BLIS BiCePS Linear Integer Solver

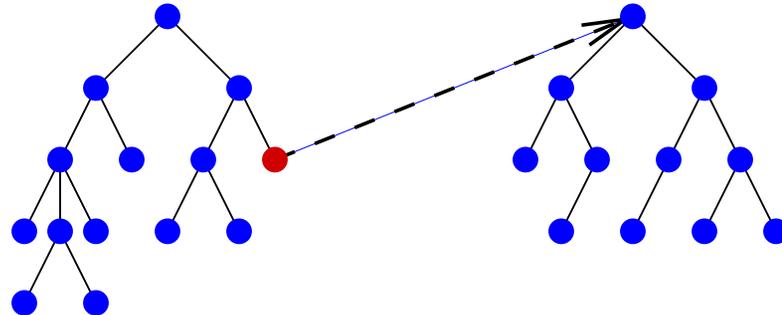
- Implementation of BCP algorithm.
- Objects are the inequalities.

Scalability Issues for Parallel Search

- Unit of work (granularity)
- Number and location of knowledge bases
- Synchronous vs. asynchronous messaging
- Ramp-up/ramp-down time

Scalability: Granularity

Work unit is a subtree.



Advantages:

- less communication.
- more compact storage via differencing.

Disadvantage:

- more possibility of non-critical work being done.

Scalability: Master - Hubs - Workers Paradigm

Master

- has global information (node **quality** and **distribution**).
- balances load between hubs.
- balances **quantity** *and* **quality**.

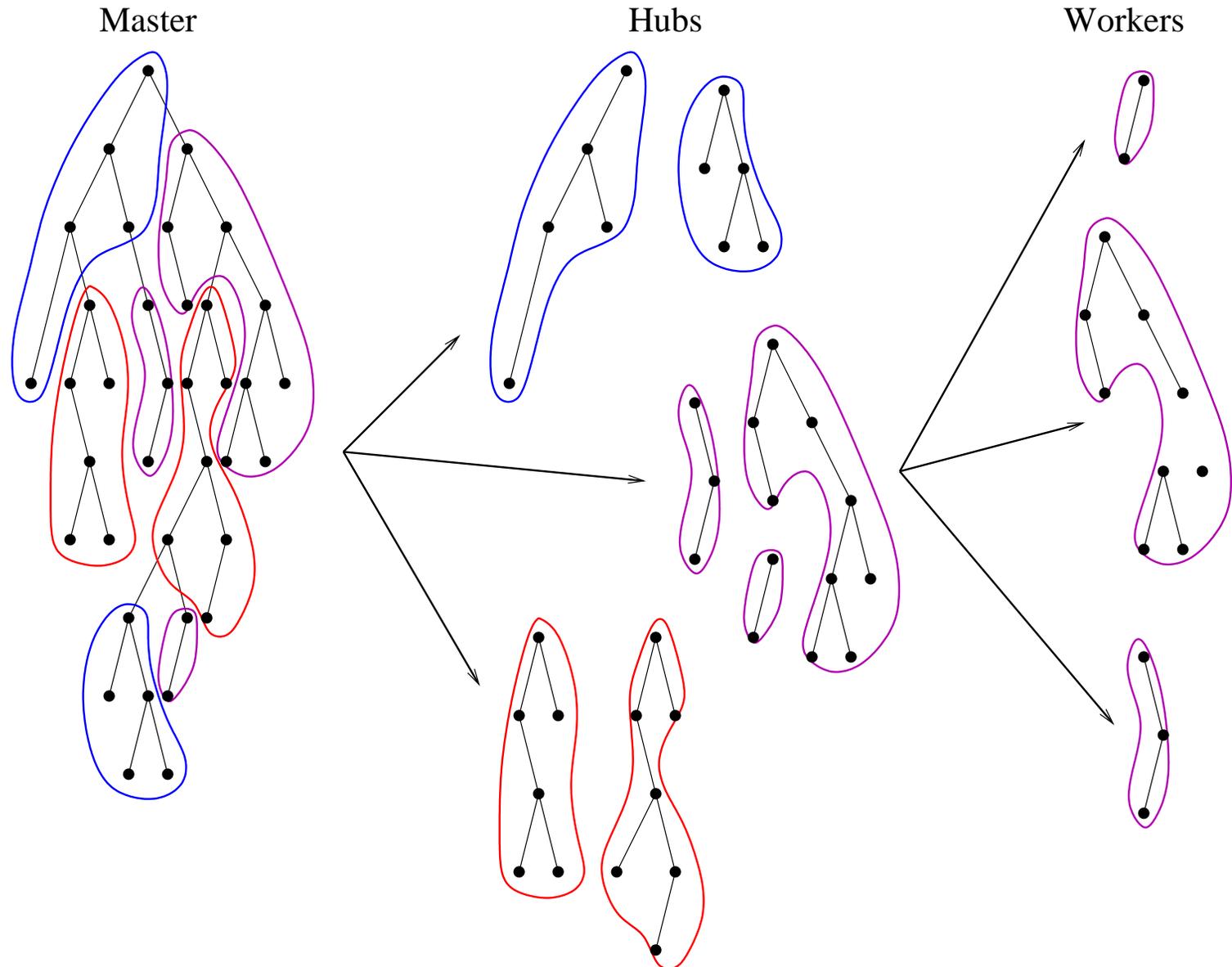
Hubs

- manage **collections of subtrees** (may not have full descriptions)
- balances load between workers

Workers

- **processes one subtree**.
- hub can interrupt.
- sends branch and quality information to hub.

Scalability: Master - Hubs - Workers Paradigm



Scalability: Asynchronous Messaging

Possible communication bottlenecks:

- **Too many messages.**
 - avoided by the increased task granularity.
 - master-hub-worker paradigm also contributes.
- **Too much synchronization** (handshaking)
 - almost no handshaking.
 - must take place when a worker finishes exploring a subtree.

Scalability: Ramp-up/Ramp-down

- Ramp-up time: Time until all processors have useful work to do.
- Ramp-down time: Time during which there is not enough work for all processors.
- Ramp-up time is perhaps **the most important scalability issue** for branch and bound when the bounding is computationally intensive.
- **Controlling Ramp-up/ramp-down**
 - Branch more quickly.
 - Use different branching rules (branch more quickly).
 - Hub instructs workers when to change rules.

Data Handling

- Focused on **data-intensive** applications.
- Need to deal with **HUGE** numbers of objects.
- **Duplication** is a big issue.
- Goal is to avoid such duplication in generation and storage.
- Implementation:
 1. Object arrives in encoded form with hash value.
 2. Object is looked up in hash map.
 3. If it does not exist, then it is inserted.
 4. A pointer to the unique copy in the hash map is added to the list.

Object Pools

- Share objects across nodes in the tree.
- **Object pools** allow generated objects to be shared.
 - Cut pool is one example.
- **Quality measures** ensure only the most “**important**” objects are retained and utilized.
- **Object encoding** is used to ensure that objects are stored only once.

Preliminary Computational Results

- Performance measures
 - Speedup
 - Number of nodes in the search tree
 - Amount of idle time
 - Total parallel overhead
 - CPU vs. Wallclock Time
- These results are with a previous generation of the software called **SYMPHONY** employing many of the same ideas, but with a single node pool.
- The application is the **Vehicle Routing Problem**.
- The platform is a Beowulf cluster running Linux with 48 dual-processor nodes.
- IBM's Optimization Subroutine Library (OSL) was used for some of the numerical analysis.

Preliminary Computational Results

Instance	Tree Size	Ramp Up	Ramp Down	Idle (Nodes)	Idle (Cuts)	CPU sec	Wallclock
A – n37 – k6	9684	0.28	1.41	8.83	29.21	947.41	248.66
A – n39 – k5	1128	0.38	0.13	1.03	5.70	158.84	41.97
A – n39 – k6	445	0.47	0.03	0.30	0.64	27.85	7.45
A – n44 – k6	1247	0.30	0.16	1.28	4.47	336.66	86.38
A – n45 – k6	1202	0.30	0.18	0.94	4.70	300.00	77.40
A – n46 – k7	33	0.42	1.39	1.09	0.22	9.82	2.97
A – n48 – k7	4931	0.68	0.83	5.12	17.65	1097.77	282.85
A – n53 – k7	1521	0.64	0.18	1.66	9.50	542.19	138.98
A – n55 – k9	9802	0.69	1.97	11.76	25.23	1990.86	508.84
A – n65 – k9	14593	0.89	4.56	21.85	104.18	8407.69	2138.54
B – n45 – k6	4243	0.45	0.57	4.03	9.85	531.04	138.15
B – n51 – k7	603	0.35	0.03	0.39	0.60	82.51	22.03
B – n57 – k7	2964	0.41	0.62	2.25	5.38	462.13	123.09
B – n64 – k9	86	0.64	0.50	0.50	0.23	16.24	4.49
B – n67 – k10	16924	0.60	4.28	17.69	96.48	3135.88	814.65
Total	69406	7.52	16.85	78.73	314.03	18046.89	4636.45
Total	64520	27.10	23.01	78.94	363.38	15128.37	1963.59
Total	85465	93.92	67.02	106.16	737.39	19836.47	1316.03
Total	75011	373.49	100.35	111.71	1600.49	17881.11	633.12

Preliminary Conclusions

- We can already achieve close to **linear speedup** or better with up to 32 processors, even with a single node pool.
- Performance of non-critical work is not a problem – the number of nodes examined stays and the total CPU time is approximately constant.
- For this small number of processors, the node pool central node pool is not a bottleneck.
- **Object pools** and **Ramp-up time** are the primary scalability issue for these **data-intensive** algorithms.
 - For BCP, the inequality pools are the biggest bottleneck.
 - We can try to control this by scaling the number of pools.
 - Ramp up time is more difficult to control.

What's Currently Available

- **SYMPHONY**: C library for implementing BCP
 - User fills in stub functions.
 - Supports shared or distributed memory.
 - Documentation and source code available www.BranchAndCut.org.
- **COIN/BCP**: C++ library for implementing BCP
 - User derives classes from library.
 - Documentation and source code available www.coin-or.org.
- **ALPS/BiCePS/BLIS**
 - In development and not yet freely available.
 - Will be distributed from CVS at www.coin-or.org.
- The **COIN-OR** repository www.coin-or.org

Applications

- **SYMPHONY** has been used for various combinatorial problems:
 - Traveling Salesman Problem
 - Vehicle Routing Problem
 - Capacitated Network Routing
 - Airline Crew Scheduling
- **SYMPHONY** is also being adapted for constraint programming.
- **COIN/BCP** has also been used for combinatorial problems
 - Minimum Weight Steiner Tree
 - Max Cut
 - Multi-knapsack with Color Constraints
- We have a number of new applications under development.

The COIN-OR Project

- Supports the development of [interoperable, open source software](#) for operations research.
- Maintains a [CVS repository](#) for open source projects.
- Supports [peer review](#) of open source software as a supplement to the open literature.
- Software and documentation is freely downloadable from www.coin-or.org