Distributed and Parallel Technology

Parallel Program Design & Algorithmic Skeletons

Hans-Wolfgang Loidl

School of Mathematical and Computer Sciences
Heriot-Watt University, Edinburgh

Semester 2 — 2016/17

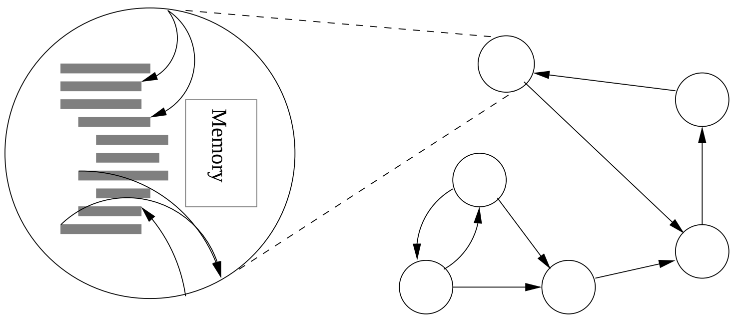
[0] Based on earlier versions by Greg Michaelson and Patrick Maier

Part I: Parallel Program Design

We follow

- Ian Foster. *Designing & Building Parallel Programs: Concepts & Tools for Parallel Software Engineering*, Addison-Wesley, 1995
  - DBPP Online: `http://www.mcs.anl.gov/~itf/dbpp/`

Parallel Programming Model



Model: *tasks* connected by *channels*

- well-suited for distributed memory architectures (and MPI)
- see DBPP Online, Part I, Chapter 1.3

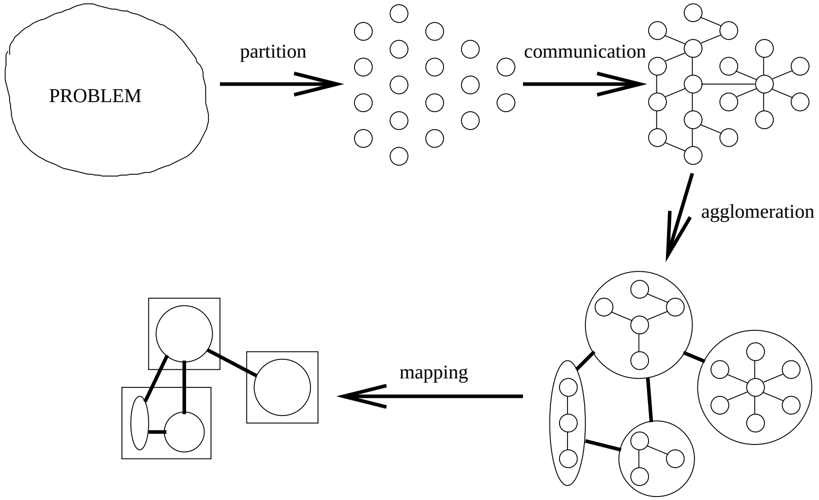
Parallel Programming Model — **Tasks**

- Parallel computation = set of concurrently executing tasks
- Task = sequential program + local memory + inports + outports
- Tasks can
  - compute (in local memory),
  - send messages to outports or receive messages from inports,
    - Sending is non-blocking but receiving is blocking.
  - create new tasks or terminate.
    - #Tasks can vary dynamically during program execution.
- Multiple tasks can be mapped to physical processors.
  - Mapping does not affect the program semantics.

Parallel Programming Model — **Channels**

- Channel = outport (task T_1) + message queue + inport (task T_2)
  - Channels are *uni-directional* (from T_1 to T_2)
  - Messages are *ordered* (FIFO order)
- Communication topology can vary dynamically.
  - Channels can be created and deleted.
  - References to channels (ports) can be sent in messages, i.e. channels are *first class objects*.

Designing Parallel Algorithms



Methodology

- see DBPP Online, Part I, Chapter 2

Designing Parallel Algorithms — **Partition**

Goal: Identify parallel tasks — *the more the better*.

Methods:

- Domain decomposition: divide data
  - E.g. matrix decomposition
- Functional decomposition: divide computation
  - E.g. pipeline

Good Design checklist:

- Does #tasks scale with problem size?
  - Or else algorithm will not scale.
- Tasks of comparable size?
  - Or else load balancing will be hard.
- Does partition avoid redundant computation/storage?
  - Or else algorithm may not scale.
- #tasks $> 10 *$ #processors?
  - Or else there will not be much left to design in later stages.
- Are there alternative partitions?

Designing Parallel Algorithms — **Communication**

Goal: Identify channels — *the less the better*.

Guidelines:

- Prefer *local* over *global* communication.
  - Distribute global comm via divide-and-conquer (e.g. merge sort)
- Compute *and communicate* concurrently (*latency hiding*).
  - Re-order computation and communication.
  - Consider asynchronous (request/response) communication.

Good Design checklist:

- All tasks perform about the same number of comm operations?
  - If not try to distribute comm operations more equitably.
- Each task communicates only with few neighbours?
  - If not try to distribute global communication.
- Are communication operations able to proceed concurrently?
  - If not try to parallelise using divide-and-conquer.
- Are tasks able to compute concurrently?
  - If not try reordering communication and computation, or try a different algorithm.

Designing Parallel Algorithms — **Agglomeration**

Goal: Combine tasks — to *improve performance* or reduce devel cost.

Guidelines:
Maintain scalability while

- Increasing locality
  - By grouping senders and receivers of data together.
  - By replicating data/computation.
- Decreasing granularity
  - By changing domain decomposition.
- Re-using sequential code

Note: Agglomeration will in general yield more tasks than processors.

- If #tasks = #processors skip *Mapping* step.

Designing Parallel Algorithms — **Agglomeration**

Good Design checklist:

- Is communication cost reduced and locality increased?
- Does benefit of replicated computation outweigh cost?
- Does replicated data compromise scalability?
  - E.g. not scalable if replicated data grows linearly in #processors.
- Are tasks similar in computation and comm costs?
- Does #tasks still scale with problem size?
- Is there still sufficient parallelism?
  - Beware: Ultimate goal is efficiency, not maximum parallelism!
- Could tasks be agglomerated further?
  - Other things being equal, coarser granularity increases efficiency.
- Development cost of modifying existing sequential code?

Designing Parallel Algorithms — **Mapping**

Goal: Assign tasks to procs — *maximise utilisation & minimise comm*

Methods:

- Static task allocation:
  - 1 task/proc is optimal for regular computation cost
    - E.g. parallelisation by domain decomposition
- Dynamic task allocation (aka. scheduling):
  - For programs with irregular computation cost, irregular communication irregular, or dynamically variable #tasks.
    - Requires order of magnitude more tasks than processors.
  - Centralised allocation:
    - Master sends tasks to fixed pool of workers.
    - **Note:** Good locality but master can become bottleneck.
  - Distributed allocation:
    - Each processor may *pull* tasks from or *push* tasks to neighbours.
    - Strategy (who to push to/pull from) may be probabilistic.
    - **Note:** Good scalability but hard to maintain locality.

Designing Parallel Algorithms — **Mapping**

Good Design checklist:

- Is there a rationale for picking static or dynamic allocation?
- Is the centralised scheduler likely to become a bottleneck?
- Is there a rationale for picking the chosen distributed scheduling strategy?
- Is #tasks large enough to guarantee balanced loads?
  - Particularly important for probabilistic strategies.

Part II: Parallel Programming Design Patterns

We follow

- T. Mattson, B. Sanders, B. Massingill. *Patterns for Parallel Programming*, Addison-Wesley, 2005
  - Complement's Foster's approach
- C. Campbell, R. Johnson, A. Miller, S. Toub. *Parallel Programming with Microsoft .NET — Design Patterns for Decomposition and Coordination on Multicore Architectures*, Microsoft Press. August 2010.
  - Implements parallel patterns in C#
  - Available online as `http://msdn.microsoft.com/en-us/library/ff963553.aspx`

Design Stages

4 stages:

1. Finding Concurrency
2. Algorithm Structure
3. Supporting Structures
4. Implementation Mechanisms

We will focus on (1) and (2).

- (3,4) recommended reading for design/implementation details.

Finding Concurrency

3 classes of patterns:

1. Decomposition Patterns
   - Task decomposition: decomp problem into concurrent tasks
   - Data decomposition: decomp data into independent units
2. Dependency Analysis Patterns
   - identify task dependencies (emphasis on data sharing)
   - group/order tasks
3. Design Evaluation
   - *not* a pattern
   - similar to Foster's *good design* checklists

Algorithm Structure

3 classes of patterns:

1. Organise by Task Decomposition
   - *Linear:* Task Parallelism
   - *Recursive:* Divide & Conquer
2. Organise by Data Decomposition
   - *Linear:* Geometric Decomposition
     - E.g. lists, vectors, matrices
   - *Recursive:* Recursive Data
     - E.g. trees
3. Organise by Data Flow
   - *Regular:* Pipeline or task DAG
     - static communication structure
   - *Irregular:* Event-based co-ordination
     - dynamic (often unpredictable) communication structure

Part III: Algorithmic Skeletons

Resources:

- Murray I. Cole. *Algorithmic Skeletons: Structured Management of Parallel Computation*, MIT Press, 1989
  - Cole's PhD thesis, first characterisation of skeletons.
  - `http://homepages.inf.ed.ac.uk/mic/Pubs/skeletonbook.ps.gz`
- *Skeletal Parallelism* homepage
  - `http://homepages.inf.ed.ac.uk/mic/Skeletons/`

Algorithmic Skeletons — What?

A *skeleton* is

- a useful pattern of parallel computation and interaction,
- packaged as a *framework/second order/template* construct (i.e. parametrised by other pieces of code).
- *Slogan:* Skeletons have *structure* (coordination) but lack *detail* (computation).

Each skeleton has

- one interface (e.g. generic type), and
- one or more (architecture-specific) implementations.
  - Each implementations comes with its own *cost model*.

A skeleton *instance* is

- the code for computation together with
- an implementation of the skeleton.
  - The implementation may be shared across several instances.

Note: Skeletons are more than design patterns.

Algorithmic Skeletons — How and Why?

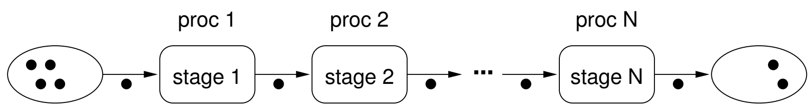
Programming methodology:

1. Write sequential code, identifying where to introduce parallelism through skeletons.
2. Estimate/measure sequential processing cost of potentially parallel components.
3. Estimate/measure communication costs.
4. Evaluate cost model (using estimates/measurements).
5. Replace sequential code at sites of useful parallelism with appropriate skeleton instances.

Pros/Cons of skeletal parallelism:

+ simpler to program than unstructured parallelism
+ code re-use (of skeleton implementations)
+ structure may enable optimisations
- *not* universal

Common Skeletons — Pipeline



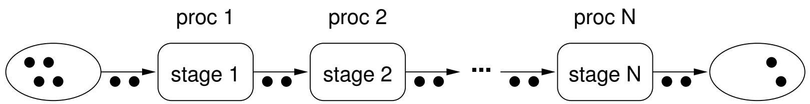
- Data flow skeleton
  - Data items pass from stage to stage.
  - All stages compute in parallel.
  - Ideally, pipeline processes many data items (e.g. sits inside loop).

Pipeline — Load Balancing

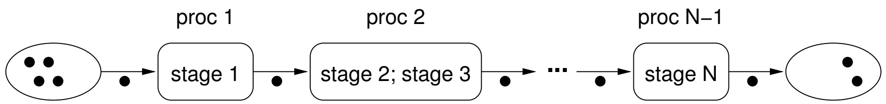
Typical problems:

1. Ratio communication/computation too high.
2. Computation cost not uniform over stages.

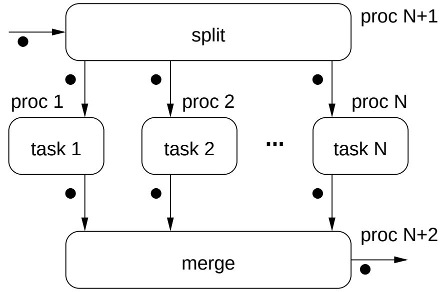
Ad (1) Pass chunks instead of single items



Ad (1,2) Merge adjacent stages

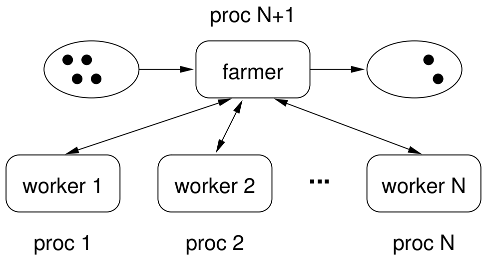


Common Skeletons — Parallel Tasks



- Data flow skeleton
  - Input split on to fixed set of (different) tasks.
  - Tasks compute in parallel.
  - Output gathered and merged together.
    - Split and merge often trivial; often executed on proc 1.
- Dual (in a sense) to pipeline skeleton.
- **Beware:** Skeleton name non-standard.

Common Skeletons — Task Farm

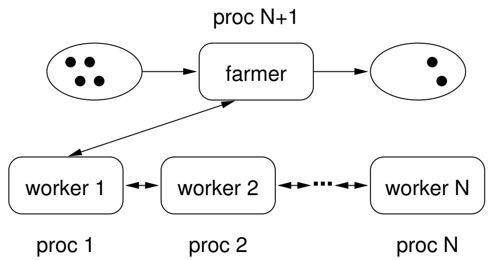


- Data parallel skeleton (e.g. parallel sort scatter phase)
  - Farmer distributes input to a pool of N identical workers.
  - Workers compute in parallel.
  - Farmer gathers and merges output.
- Static vs. dynamic task farm:
  - *Static:* Farmer splits input once into N chunks.
    - Farmer may be executed on proc 1.
  - *Dynamic:* Farmer continually assigns input to free workers.

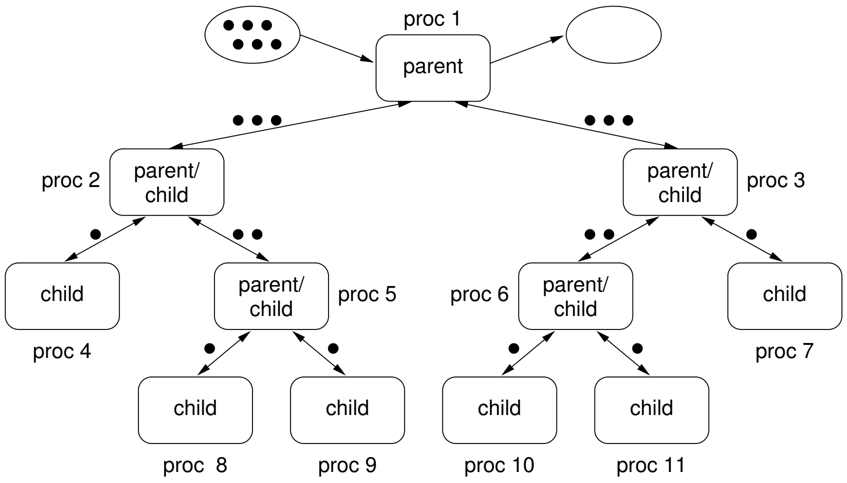
Task Farm — Load Balancing

Typical problems:

1. Irregular computation cost (worker).
   - Use dynamic rather than static task farm.
   - Decrease chunk size: Balance granularity vs. comm overhead.
2. Farmer is bottleneck.
   - Use self-balancing *chain gang* dynamic task farm.
     - Workers organised in linear chain.
     - Farmer keeps track of # free workers, sends input to first in chain.
     - If worker busy, sends data to next in chain.



Common Skeletons — Divide & Conquer



- Recursive algorithm skeleton (e.g. parallel sort merge phase)

Common Skeletons — Divide & Conquer II

- Recursive algorithm skeleton
  - Recursive call tree structure
    - Parent nodes *divide* input and pass parts to children.
    - All leaves compute the same sequential algorithm.
    - Parents gather output from children and *conquer*, i.e. combine and post-process output.
- To achieve good load balance:
  1. Balance call tree.
  2. Process data in parent nodes as well as at leaves.

Skeletons in the Real World

Skeletal Programming

- can be done in many programming languages,
  - skeleton libraries for C/C++
  - skeletons for functional languages (GpH, OCaml, ...)
  - skeletons for embedded systems
- is still not mainstream,
  - Murray Cole. *Bringing Skeletons out of the Closet*, Parallel Computing 30(3) pages 389–406, 2004.
  - González-Vélez, Horacio and Leyton, Mario. *A survey of algorithmic skeleton frameworks: high-level structured parallel programming enablers*, Software: Practice and Experience 40(12) pages 1135–1160, 2010.
- but an active area of research.
  - $>$ 30 groups/projects listed on skeleton homepage
- and it is slowly becoming mainstream
  - TPL library of Parallel Patterns in C# (blessed by Microsoft)

Part IV: Implementing Skeletons

Skeletons Are Parallel Higher-Order Functions

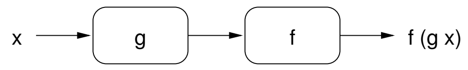
Observations:

- A *skeleton* (or any other template) is essentially a higher-order function (HOF), ie. a function taking functions as arguments.
  - Sequential code parameters are functional arguments.
- Skeleton implementation is parallelisation of HOF.
- Many well-known HOFs have parallel implementations.
  - Thinking in terms of higher-order functions (rather than explicit recursion) helps in discovering parallelism.

Consequences:

- Skeletons can be combined (by function composition).
- Skeletons can be nested (by passing skeletons as arguments).

Skeletons Are PHOFs — Pipeline



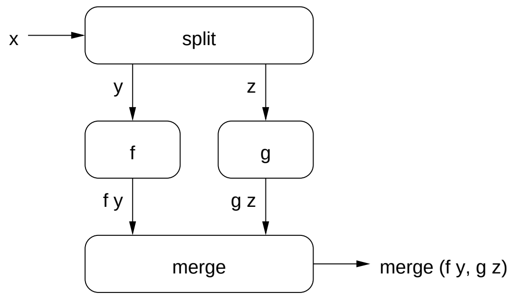
Code (parallel implementation in red)

```
pipe2 :: (b -> c) -> (a -> b) -> a -> c
pipe2 f g x = let y = g x in
              y `par` f y
```

Notes:

- `pipe2` is also known as *function composition*.
- In Haskell, sequential function composition is written as `.` (read “dot”).

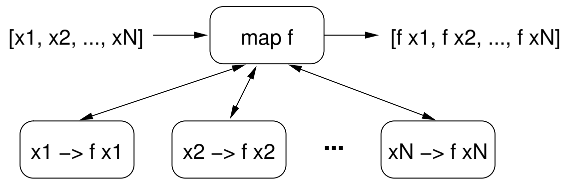
Skeletons Are PHOFs — Parallel Tasks



Code (parallel implementation in red)

```
task2 :: (a -> (b,c)) -> (d -> e -> f) -> (b -> d) -> (c -> e) -> a -> f
task2 split merge f g x = let (y,z) = split x
                              fy = f y
                              gz = g z in
                          fy `par` gz `pseq` merge fy gz
```


Skeletons Are PHOFs — Task Farm



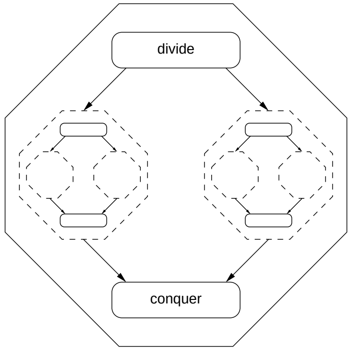
Code (parallel implementation in red)

```
farm :: (a -> b) -> [a] -> [b]
farm f []     = []
farm f (x:xs) = let fx = f x in
                fx `par` fx : (farm f xs)
```

Notes:

- `farm` is also known as *parallel map*.
  - Map functions exist for many data types (not just lists).
- Missing in implementation: strategy to force eval of lazy list.
- Strategies also useful to increase granularity (by chunking).

Skeletons Are PHOFs — Divide & Conquer



Code (parallel implementation in red)

```
dnc :: (a -> (a,a)) -> (b -> b -> b) -> (a -> Bool) -> (a -> b) -> a -> b
dnc div conq atomic f x | atomic x  = f x
                        | otherwise = let (l0,r0) = div x
                                          l = dnc div conq atomic f l0
                                          r = dnc div conq atomic f r0 in
                                      l `par` r `pseq` conq l r
```


Skeletons Are PHOFs — Divide & Conquer

Notes:

- Divide & Conquer is a generalised *parallel fold*.
  - Folds exist for many data types (not just lists).
- Missing in impl: strategies to force eval and improve granularity.

Aside: folding/reducing lists

```
fold :: (a -> a -> a) -> a -> [a] -> a
-- fold f e [x1,x2,...,xn] == e `f` x1 `f` x2 ... `f` xn, provided that
-- (1) f is associative, and
-- (2) e is an identity for f.

-- Tail-recursive sequential implementation:
fold f e []     = e
fold f e (x:xs) = fold f (e `f` x) xs

-- Parallel implementation as instance of divide & conquer:
fold f e = dnc split f atomic evalAtom where
    split xs = splitAt (length xs `div` 2) xs
    atomic []  = True
    atomic [_] = True
    atomic _   = False
    evalAtom []  = e
    evalAtom [x] = x
```

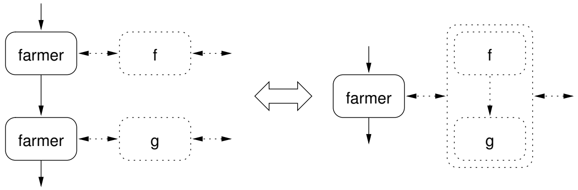

Program Transformations

Observation:

- HOFs can be transformed into other HOFs with provably equivalent (sequential) semantics.

Example: Pipeline of farms vs. farm of pipelines

- `map g . map f == map (g . f)`



- use `map g . map f` (pipe of farms) if ratio comp/comm high
- use `map (g . f)` (farm of pipes) if ratio comp/comm low
- More transformations in
  - G. Michaelson, N. Scaife. *Skeleton Realisations from Functional Prototypes*, Chap. 5 in S. Gorlatch and F. Rabhi (Eds), *Patterns and Skeletons for Parallel and Distributed Computing*, Springer, 2002

Program Development with Functional Skeletons

Programming Methodology:

1. Write seq code using HOFs with known equivalent skeleton.
2. Measure sequential processing cost of functions passed to HOFs.
3. Evaluate skeleton cost model.
4. If no useful parallelism, transform program and go back to 3.
5. Replace HOFs that display useful parallelism with their skeletons.

Tool support:

- Compilers can automate some steps (see Michaelson/Scaife)
  - Only for small, pre-selected set of skeletons
- Example: PMLS (developed by Greg Michaelson et al.)
  - Skeletons: map/fold (arbitrarily nested)
  - Automates steps 2-5.
    - Step 2: automatic profiling
    - Step 4: rule-driven program transformation + synthesis of HOFs
    - Step 5: map/fold skeletons implemented in C+MPI

Further Reading

- Ian Foster. *"Designing & Building Parallel Programs: Concepts & Tools for Parallel Software Engineering"*, Addison-Wesley, 1995
  Online: `http://www.mcs.anl.gov/~itf/dbpp/`
- J. Dean, S. Ghemawat. *"MapReduce: Simplified Data Processing on Large Clusters"*. Commun. ACM 51(1):107–113, 2008.
  Online: `http://dx.doi.org/10.1145/1327452.1327492`
- G. Michaelson, N. Scaife. *"Skeleton Realisations from Functional Prototypes"*, Chap. 5 in S. Gorlatch and F. Rabhi (Eds), *Patterns and Skeletons for Parallel and Distributed Computing*, Springer, 2002
- Michael McCool, James Reinders, Arch Robison. *"Structured Parallel Programming"*. Morgan Kaufmann Publishers, Jul 2012. ISBN10: 0124159931 (paperback)