# Compiler Technology for Data-Parallel Languages

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International Summer School on Advances in Programming Languages Heriot-Watt University Edinburgh, Scotland

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Target Architectures and their Challenges Maior Compilation Challenges and Solutions Summary Why Data-Parallelism Matters Data-Parallel Languages and their Challenges

#### Multicores are Here!

#### Parallelism was

- academically studied for a few decades
- affordable only by HPC labs with deep pockets
- programmed by experts

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- Today Parallelism is
  - available cheaply in everybody's PCs and laptops
    - single-core CPUs are history
    - GPGPUs bring hundreds of cores for less than 100 GBP

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- Today Parallelism is
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    - single-core CPUs are history
    - GPGPUs bring hundreds of cores for less than 100 GBP
- $\Rightarrow$  Needs to be programmable by general practitioners!
- ⇒ Opportunity / Obligation for programming language research to provide adequate tools!

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#### The Dawn of a Software Revolution

- Many of the "old truths" do no longer hold!
  - Sequential Truth: redundant computations are evil!
  - Parallel Truth: redundant computation may reduce synchronisation!
  - Sequential Truth: excessive storage use is evil!
  - Parallel Truth: separation of data may eliminate dependencies!

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- $\Rightarrow$  A declarative approach is needed!

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#### Data-Parallelism

Fundamental idea:

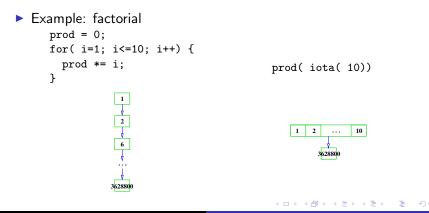
Formulate Algorithms in terms of SPACE rather than TIME

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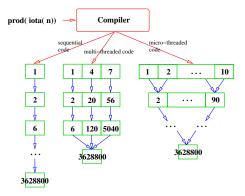
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# The Compilation Challenge — a first glimpse —



⇒ Different hardware architectures require different code generation strategies!

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# The Language Challenge

- What data structures are supported?
  - Choice I: homogeneous or inhomogeneous data?
  - Choice II: nested structure or flat?
    - if nested, homogeneously or inhomogeneously?
    - staticly known nesting depth or unlimited nesting?

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- What operations are supported?
  - Choice I: map-based only or map-based and fold-based?
  - Choice II: homogeneous or inhomogeneous?
  - Choice III: nested or flat only?

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  - Choice I: map-based only or map-based and fold-based?
  - Choice II: homogeneous or inhomogeneous?
  - Choice III: nested or flat only?
- $\Rightarrow$  Genericity vs Efficiency Dilemma!

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# A Collection of Choices Made

- ► APL / J/ K
- NESL
- SISAL
- ► Fortran90 / HPF
- SAC
- Google's mapreduce
- Fortress
- data-parallel Haskell

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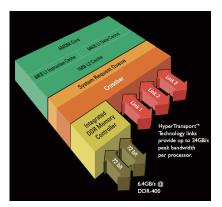
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The Compilation Challenge — a second look —

- Hardware and software constraints interfere big time! Examples:
  - Only hohmogeneous data structures benefit from vector instructions!
  - Not all architectures do support truely nested concurrency!
  - Some architectures do not cope well with inhomogeneous operations.
  - Achieving efficient fold operations typically requires architecture dependent measures.
- Getting a single aspect wrong typically is fatal.

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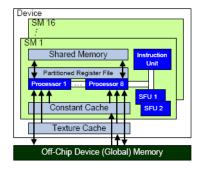
#### **Traditional SMPs**



- several standard cores (currently 2-8) on one chip
- thread handling expensive
- synchronisation expensive
- cache coherence expensive
- memory access bottleneck

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### **GPGPUs**

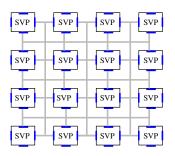


- ▶ more than 128 cores
- hardware support for thread creation and synchronisation
- hardware support for thread scheduling
- very restricted thread-functionality
- strictly flat concurrency

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card-private memory

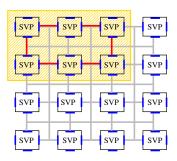
### Special Hardware, here: $\mu TC$



- several hundread full-fledged cores
- hardware support for thread creation
- hardware support for linear synchronisation
- hardware support for thread scheduling
- cash-only memory
- dynamic ressource allocation

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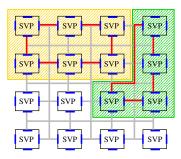


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# Challenge I: Concurrency Overhead Amortisation

typical thread overhead cost (pthreads on solaris):

- thread creation typically several thousands of cycles!
- thread switch costs more than 1000 cycles!
- semaphor-based sync typically as expensive as thread creation!

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# Measure I: Localise "Thread Management"

#### Main idea:

create a fixed set of threads, prefereably matching the number of cores available, and have a light-weight solution in the runtime system.

- + no OS thread switches needed
- + thread creation exactly once upon startup
- + lock-free synchronisations
- + cheap dynamic scheduling possible
- potential resource waste

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## Measure II: Flattening: Maximising Scheduling Flexibility

#### Main idea:

expose as much concurrency to the local thread management as possible by accumulating nested data parallel situations.

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- Blelloch and Sabot, Compiling Collection-Oriented Languages onto Massively Parallel Computers, Journal of Parallel and Distributed Computing, 1990.
- Grelck, Scholz and Trojahner, WITH-Loop Scalarization Merging Nested Array Operations, IFL'03, 2004.
- Peyton Jones, Leshchinskiy, Keller and Chakravarty, Harnessing the Multicores: Nested Data Parallelism in Haskell, FSTTCS, 2008.

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# Measure III: Dedicated Hardware Support

#### Main idea:

novel architectures such as  $\mu$ TC enable more direct exposure of data-parallelism to the hardware.

The overall gain of this approach is in the focus of current research:

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# Challenge II: Computation vs Memory Transfer

Whatever is computed by a single thread on a single node underlies the good "old truths"!

 $\Rightarrow$  exessive memory use becomes evil (again)!

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### Measure I: Transforming Space into Time

Main idea:

use producer / consumer optimisations to avoid data structures to be materialised in memory.

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- Abrams, An APL Machine, PhD thesis, 1970.
- Scholz, With-loop-folding in SAC-Condensing Consecutive Array Operations, IFL'97, 1997.
- ► Chakravarty and Keller, Functional Array Fusion, ICFP'01, 2001.
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- Russell, Mellor, Kelly and Beckmann, DESOLA: an Active Linear Algebra Library Using Delayed Evaluation and Runtime Code Generation, Science of Computer Programming, 2008.

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# Measure II: Locality Enhancing Scheduling

Main idea:

order the elements computed by a single thread in a cache efficient way.

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- Grelck, Kreye and Scholz, On Code Generation for Multi-Generator WITH-Loops in SAC, IFL'99, 2000.
- Bondhugula, Hartono, Ramanujam, and Sadayappan, A practical automatic polyhedral parallelizer and locality optimizer, PLDI'08, 2008.

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# Measure III: Latency Hiding

Main idea:

if thread-switches are cheap, we can create several threads on one core!

 $\Rightarrow$  non-memory bound computations can hide the memory latency!

Architectures like SUN's Niagra, GPGPUs or  $\mu$ TC benefit directly!

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# Challenge III: The Aggregate Update Problem

- The data-parallel approach suggests the use of many large data structures.
- It is key to leave it to the compiler to decide which/ how many are being materialised!
- $\Rightarrow$  requires a space-efficient implicit memory management!

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# Measure I: Reference Counting

#### Main idea:

keep the number of active references to any given data structure in a seperately maintained field.

 $\Rightarrow$  enables updates and memory reuse ASAP!

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  - Trojahner, Implicit Memory Management for a Functional Array Processing Language, Diploma Thesis, 2005.

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### Measure II: Concurrent Heap Management

Main idea:

keep separate heaps for separate threads

 $\Rightarrow$  lock-free concurrent memory management can be achieved.

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  - ► Joseph Attardi and Neelakanth Nadgir, A Comparison of Memory Allocators in Multiprocessors, Sun Developer Network, 2003.
  - Grelck and Scholz, Efficient Heap Management for Declarative Data Parallel Programming on Multicores, DAMP'08, 2008.

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### Open Issue: How to deal with dynamic nesting?

- current allocators are mainly effective due to restrictions in the the way threads are created / what threads do
- architectures with hardware support for thread creation / handling break these boundaries
- How do we avoid the re-introduction of lock-based memory operations?

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### Multicores will Enforce a Software Revolution

- Nobody wants to buy a new machine if he does not benefit in terms of performance!
- Hand-parallelising programs is just too hard!

# Data-Parallel Programmming defines algorithms in SPACE rather than in TIME

- Data-Parallel Programmming is not just the ability to parallelise loops without dependencies!
- It encourages different program specifications where dependencies are expressed in data rather than time!
- Iterations are expressed as vectors / arrays!
- check it out!

www.sac-home.org

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# Compiling Data-Parallel Programms is Far from Trivial

- all the black-belt knowledge of parallel programming needs to go into the compiler
- getting a seemingly minor detail wrong often prevents from performance gains
- compilion techniques are heavily dependent on the target hardware

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# Some Solutions Exist

- localised scheduling techniques
- target-dependent space time transformations
- private heap management
- ► ...
- The techniques shown here enable auto-parallelisation that easily outperforms that of Fortran90/ HPF programs!
- The first autoparallelising compilers for GPGPUs are coming into existance just now!

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#### Much More Work Needs to be Done

- Many new architectures enable new approaches
- How generic can data parallel programs be?
- How can we make use of hybrid architectures?
- Can optimisation happen at runtime?
- ...

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