Insieme

Insieme - an Optimization System for OpenMP, MPI and OpenCL Programs

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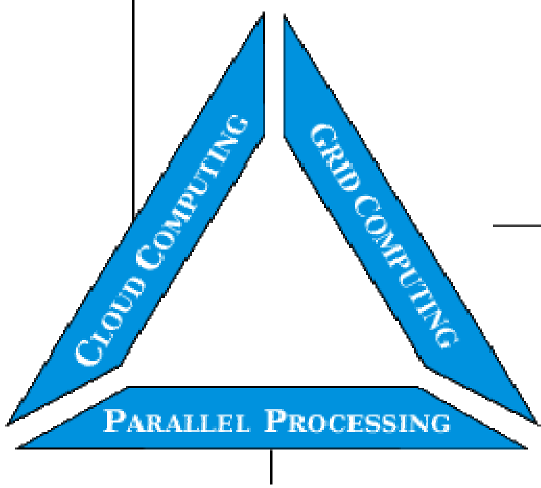
TU Munich 2011-03-30

High Performance Parallel & Distributed Computing

Our Research



Cloud Computing

- Hardware and Software Virtualisation
- Performance Modelling and Analysis
- Quality of Service
- Multi-criteria Scheduling
- Service Level Agreements

Grid Computing

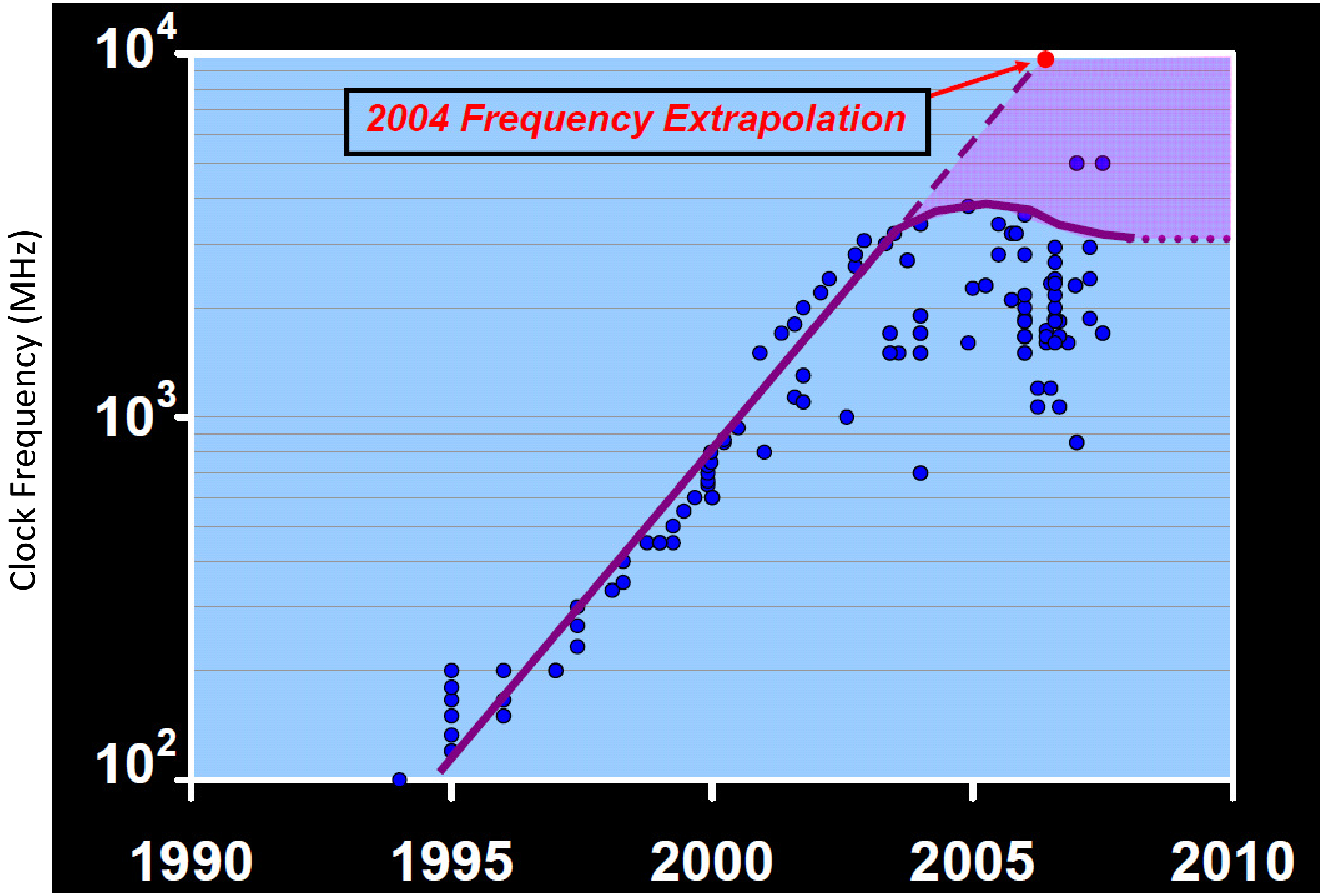
- Programming Paradigms and Methods
- Meta Scheduling
- Resource Brokerage
- Performance Measurement, Analysis and Prediction
- Ontologies for the Grid

Parallel Processing

- Programming Paradigms
- Performance Instrumentation and Measurement
- Performance Analysis and Interpretation
- Performance Prediction
- Compiler Analysis and Optimisation
- Experiment Management

Microprocessor Clock Speed Trends

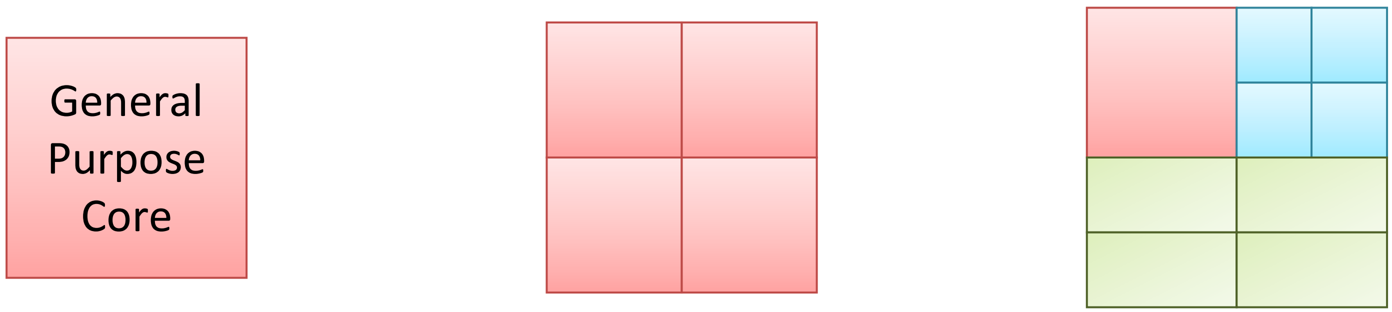
Managing power dissipation is limiting clock speed increases



Source: Michael Perrone, IBM

Hardware Architecture Evolution

Hardware

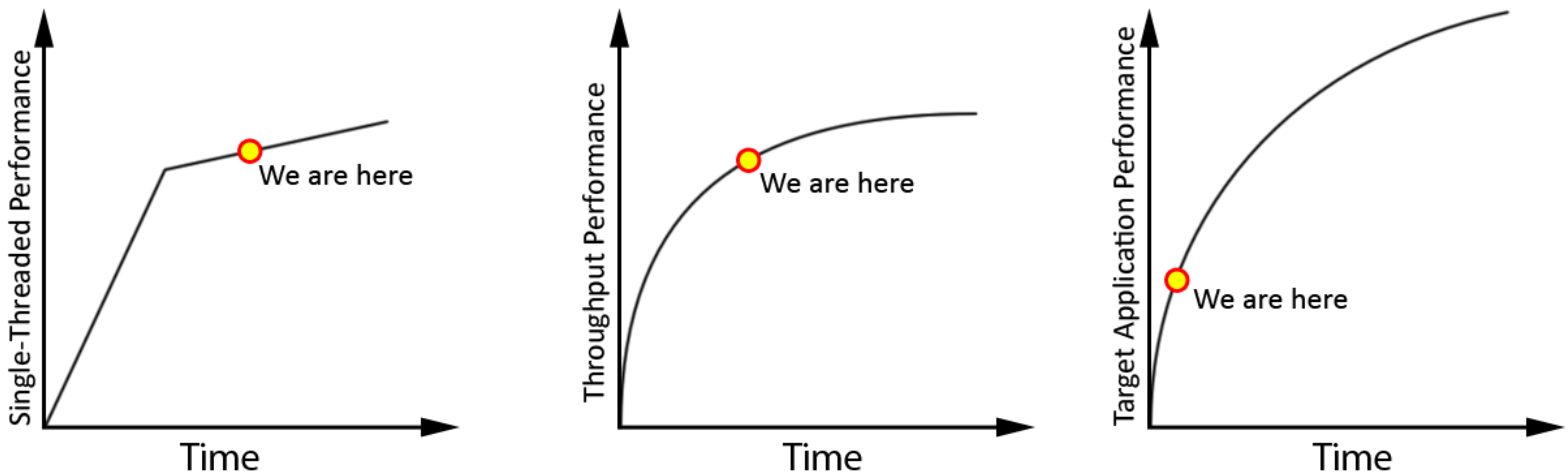


Software — Sequential — OpenMP, MPI — Hybrid OpenMP/OpenCL

Single-Core Era	Multi-Core Era	Heterogenous Many-Core Era
Constrained by: • Power • Complexity	Constrained by: • Power • Parallel software availability • Scalability	Enabled by: • Abundant data parallelism • Power-efficient GPUs Limited by: • Programming models

Source: AMD, ISSCC2010, www.anandtech.com/show/2933

Hardware Architecture Evolution



Single-Core Era

Constrained by:
- Power
- Complexity

Multi-Core Era

Constrained by:
- Power
- Parallel software availability
- Scalability

Heterogenous Many-Core Era

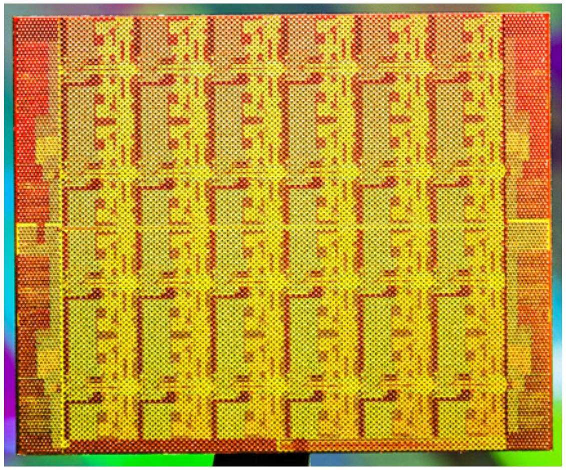
Enabled by:
- Abundant data parallelism
- Power-efficient GPUs

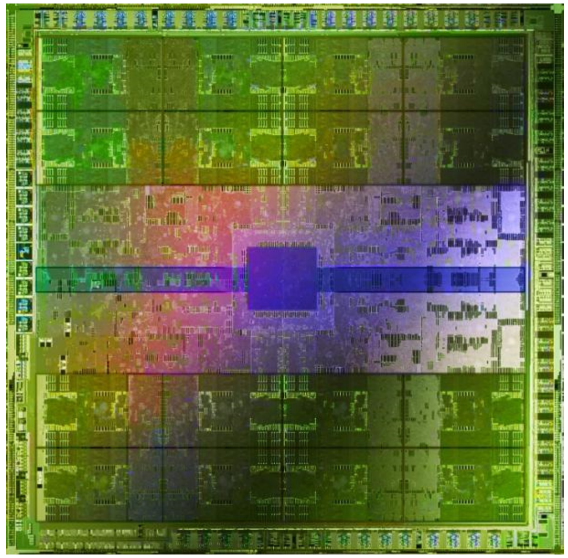
Limited by:
- Programming models

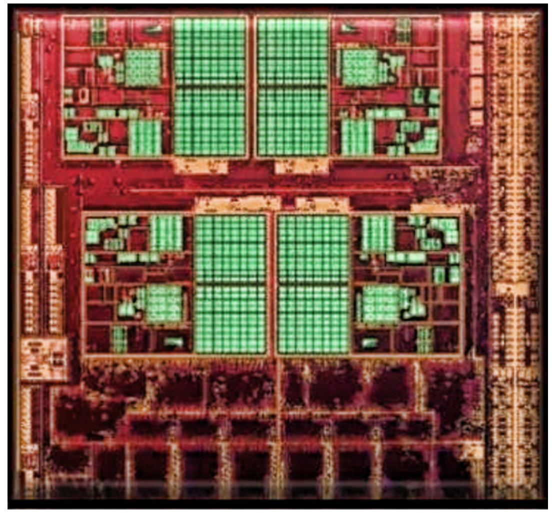
Insieme

Source: AMD, ISSCC2010, www.anandtech.com/show/2933

Future Hardware Diversity







Intel:

- "Single chip cloud computer"
- 24 dual-core tiles
- Mesh interconnect

Nvidia:

- "Fermi" GPGPU
- 512 CUDA cores
- Configurable L1 cache / scratchpad

AMD:

- "Fusion" combines GPU and CPU
- 4 CPU cores
- 480 Stream processors

Parallel Processing: Past and Future

- Parallel Processing has long been an essential component of scientific computing that drives natural and technical sciences.
- Parallel Processing appears to be merging with
  - embedded systems
  - multi-media and entertainment
  - reliable systems
  - and more to come …
- Different application domains require different parameters to be optimized:
  - performance
  - cost
  - energy
  - reliability, etc.
- This makes HPC a multi-parameter optimization problem

The Multicore Software Problem

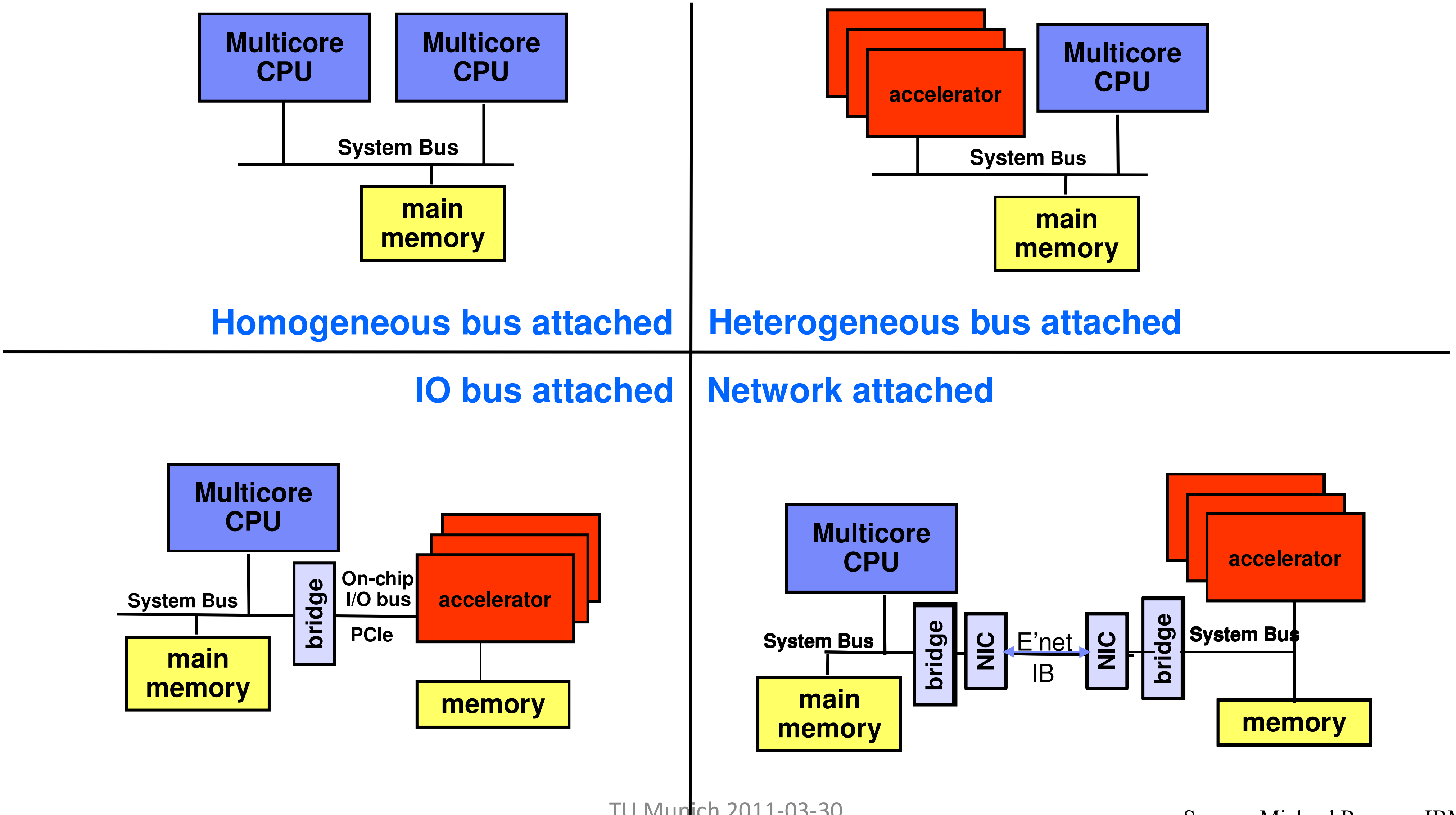
- There is more than 1 million software engineers and programmers working in the EU
- A negligible fraction know how to program parallel computers.
- Enormous legacy investment in serial programming technology and training.

"[Multicore] could become the biggest software ***remediation*** *task of this decade."*

-- Gartner Group, January 31, 2007

Current/Future Many-core Architectures

Heterogeneous cores running at different speed



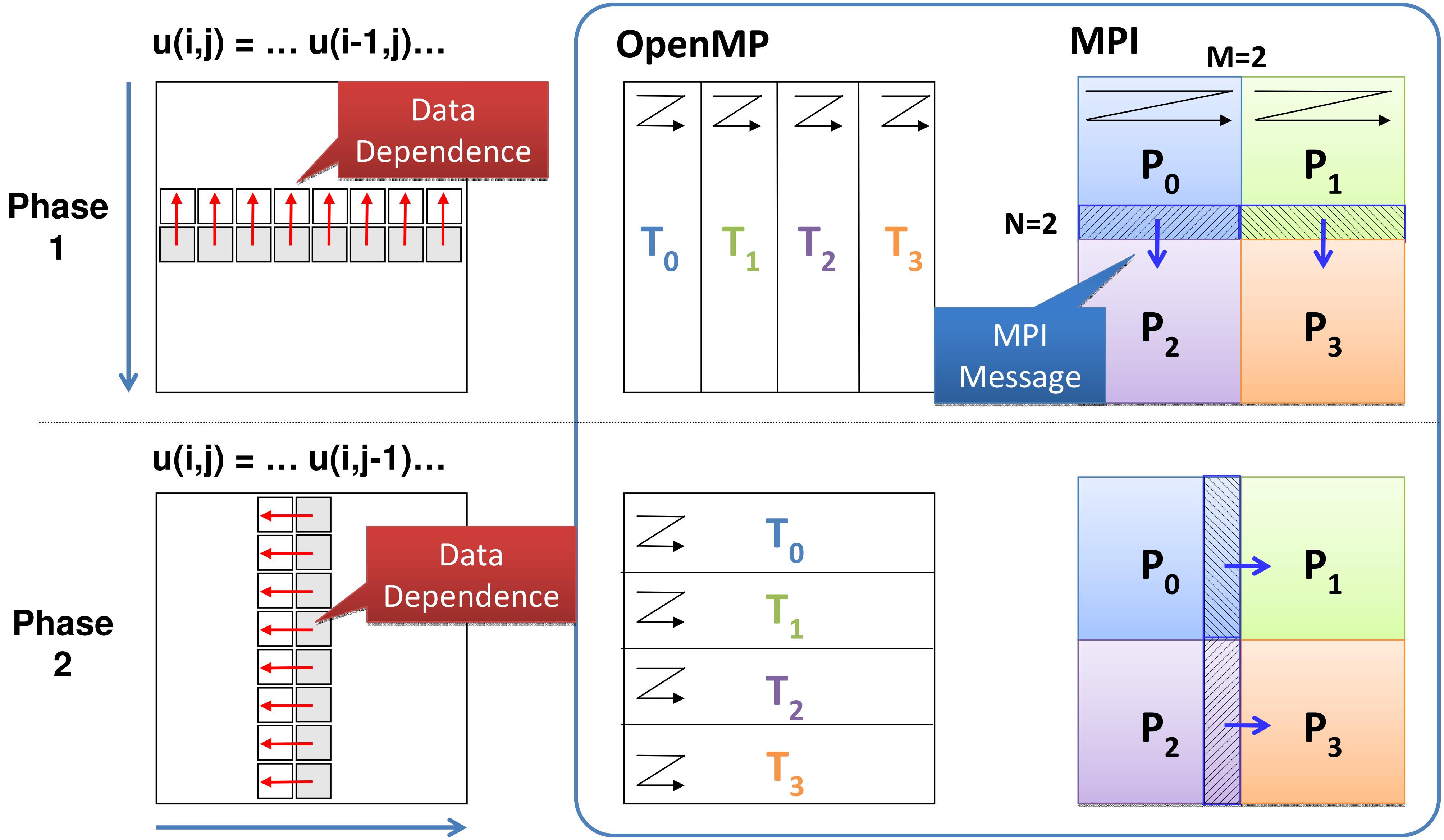
Source: Michael Perrone, IBM

Why is it so hard to optimize codes for parallel systems?

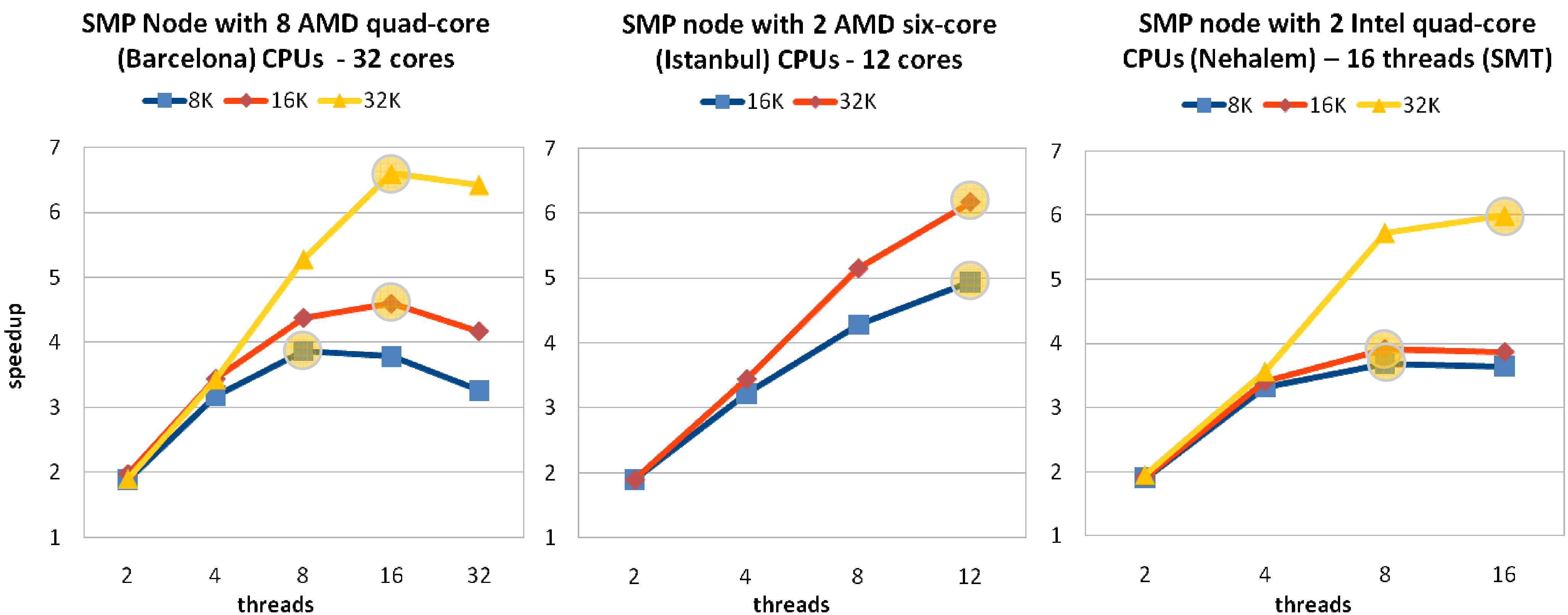
- Question:
  - If the strategy for I/O scheduling, process scheduling, cache replacement policy would be changed, how would you re-write your code?
- Complexity, undecidability and difficulty to predict program and system behavior:
  - Dynamic reallocation of cores, memory, clock frequency; external load, sharing of resources, etc.
  - Processor and system architectures are so complex that it is impossible for a human being to find best code transformation sequences
  - Operating system, external load, queuing systems, caches often have non-deterministic behavior

Example: ADI Solver (Alternating Direction Implicit)

Sequential Algorithm | **Parallelization Strategies**



ADI/OpenMP Comparison



What is the optimal number of cores to use?

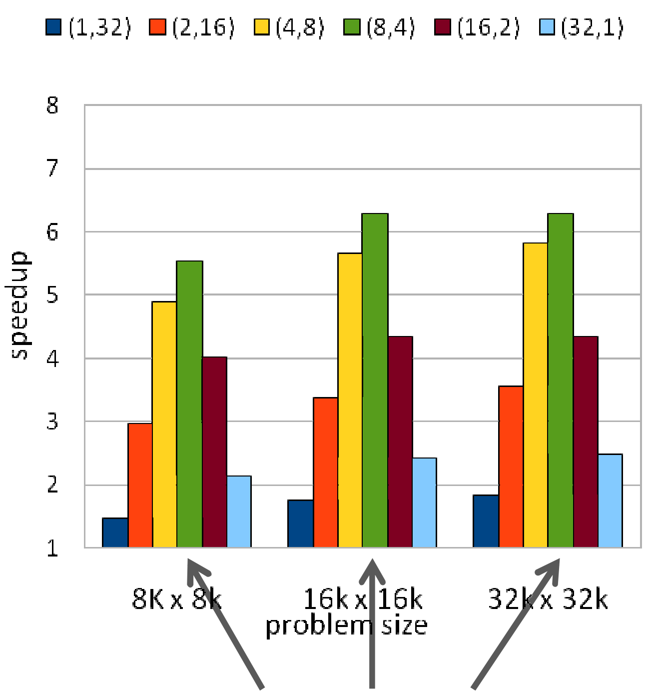
- Performance impact: CPU architecture, cache size and memory hierarchy
- Ideal number of threads requires knowledge about the program and architecture.

ADI/MPI Comparison

- Data is block-wise distributed onto set of MPI processes
- **(N,M)** → **N** row and **M** column block distribution

Total of 32 cores

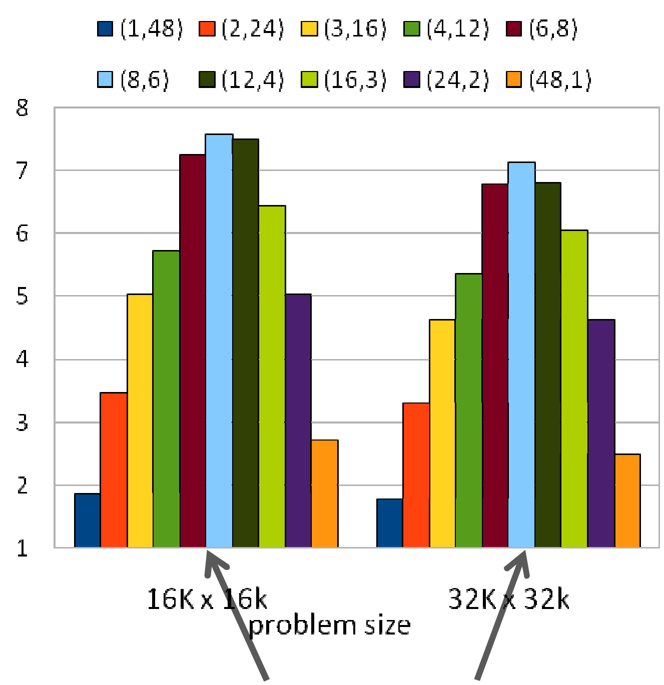
SMP node with 8 AMD quad-core (Barcelona) CPUs



optimal distribution: (8,4)

Total of 48 cores

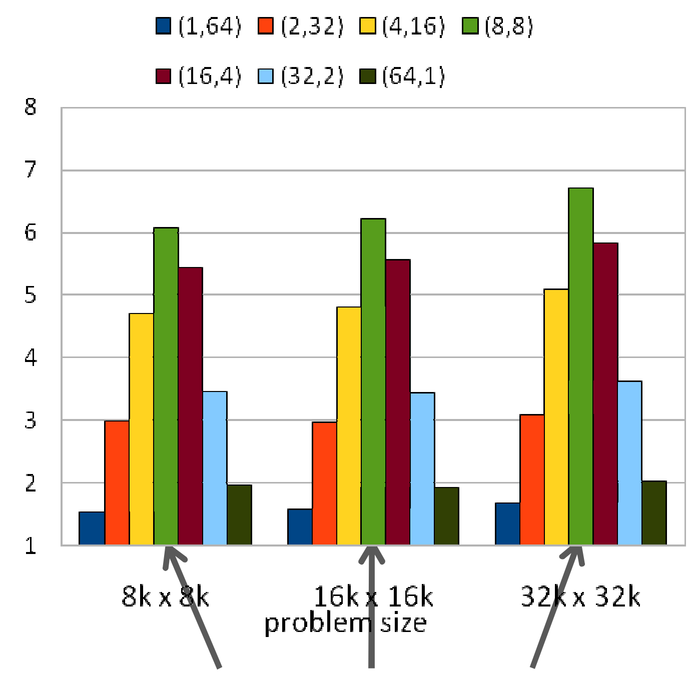
4 SMP nodes with 2 AMD six-core (Istanbul) CPUs each



optimal distribution: (8,6)

Total of 64 threads

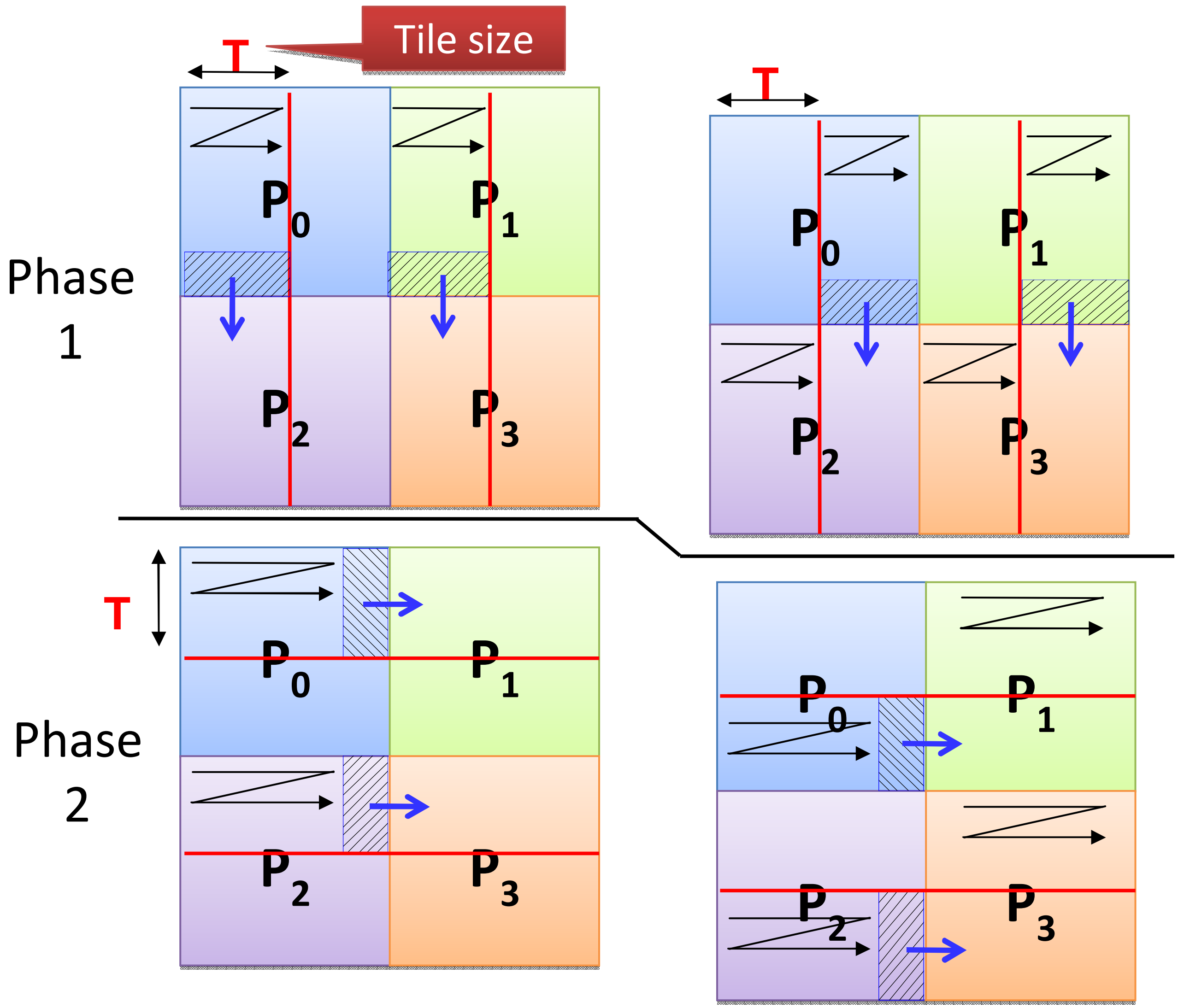
4 SMP nodes with 2 Intel quad-core (Nehalem) CPUs each (2-fold SMT)

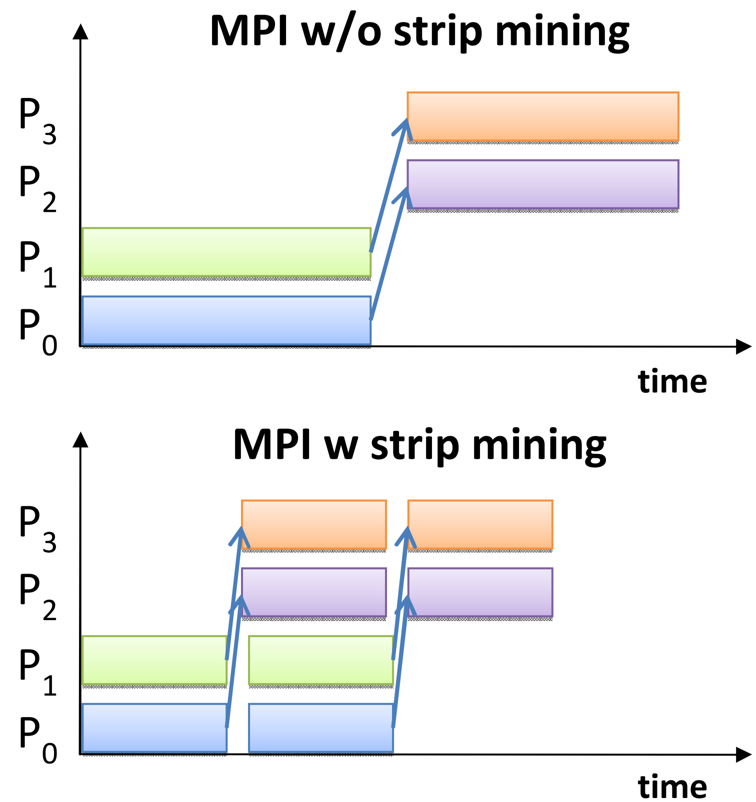


optimal distribution: (8,8)

ADI/MPI Message Strip Mining

Message strip mining enables computation pipelining for increased parallelism

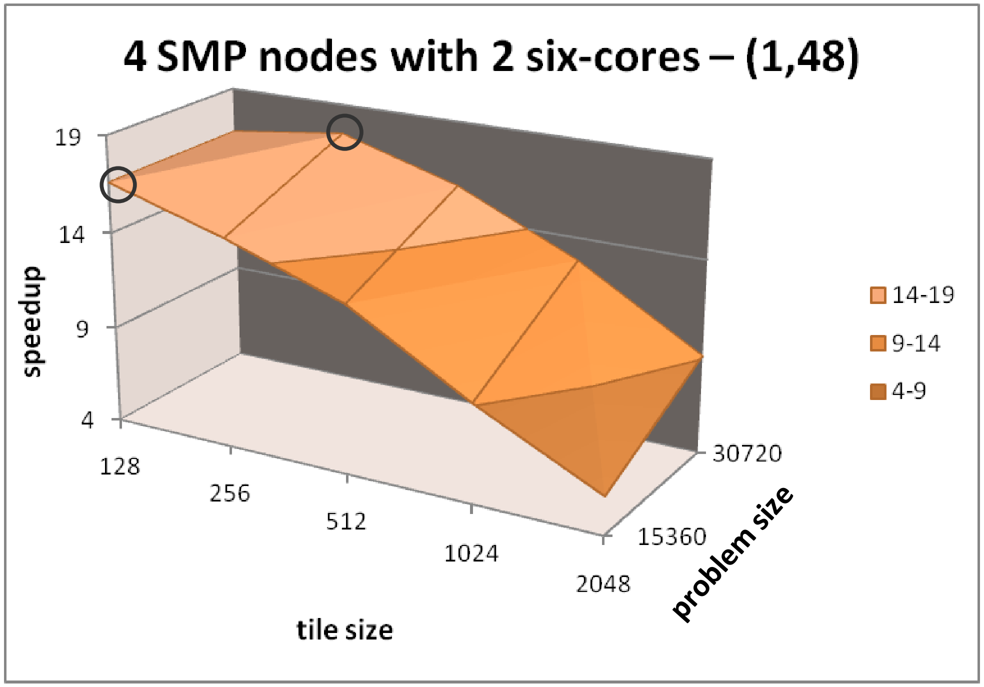


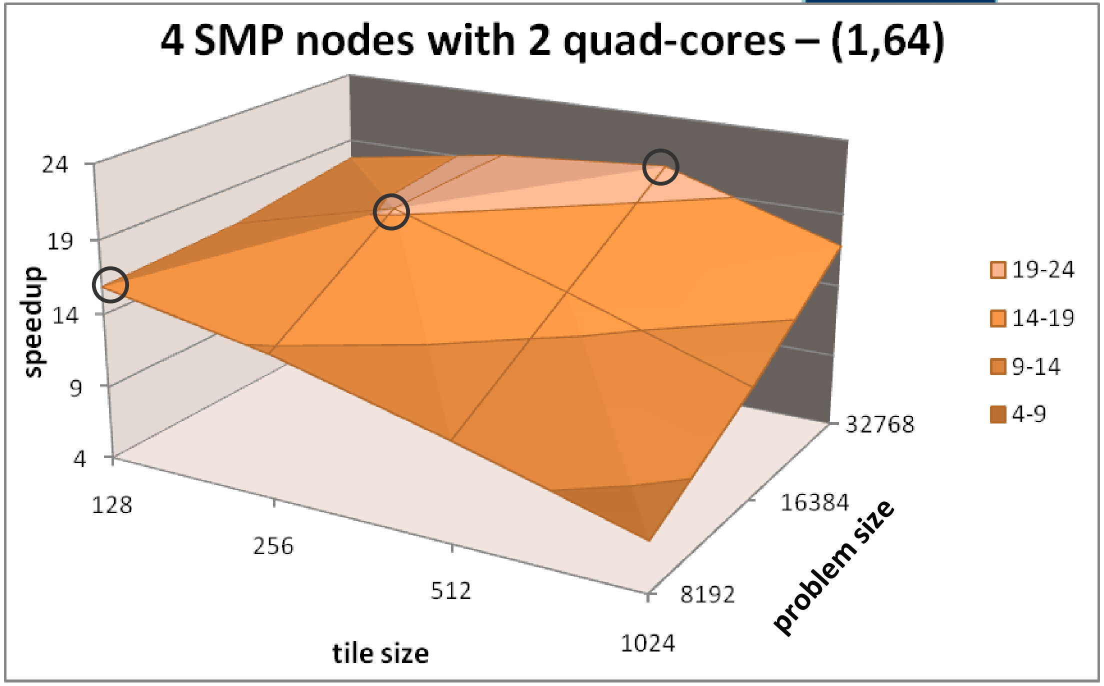


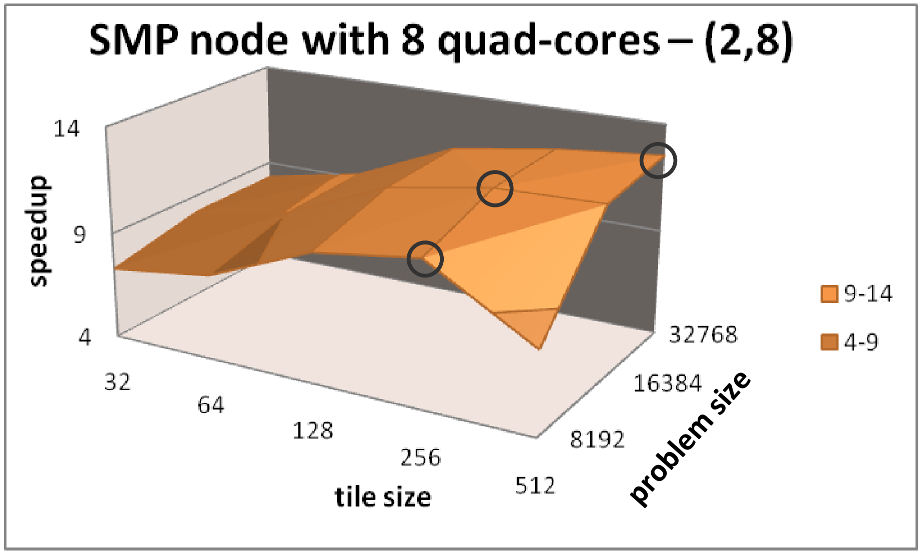
Question

What is the **optimal** tile size **T** ?

ADI/MPI Message Strip Mining







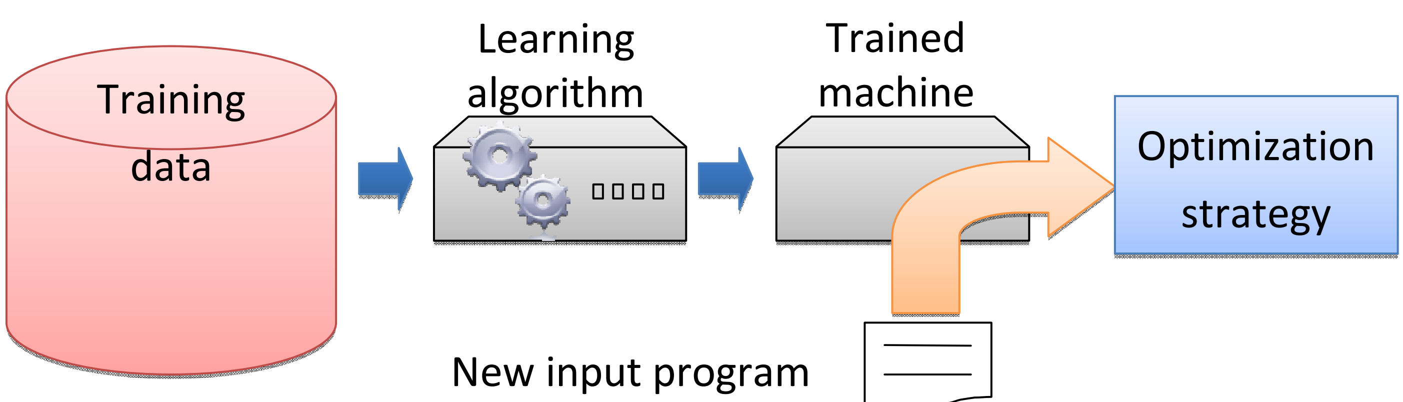
The optimal tile size for a "good" data layout depends on underlying architecture, program, problem size, etc.

The Insieme System

- A multi-parameter optimizing Compiler for MPI, OpenMP and OpenCL
  - Optimization across multi-parameters:
    - performance, cost, energy consumption, reliability, etc.
  - Sources of optimization
    - program structure (transformations)
    - runtime environment parameters
  - Analysis and optimization
    - static and dynamic analysis for entire program and code regions
    - based on historic date: executions of training kernels and applications
    - uses machine learning to deal with huge search space for combinations of optimizations
- Insieme is currently under development at the University of Innsbruck

Machine Learning based Optimization

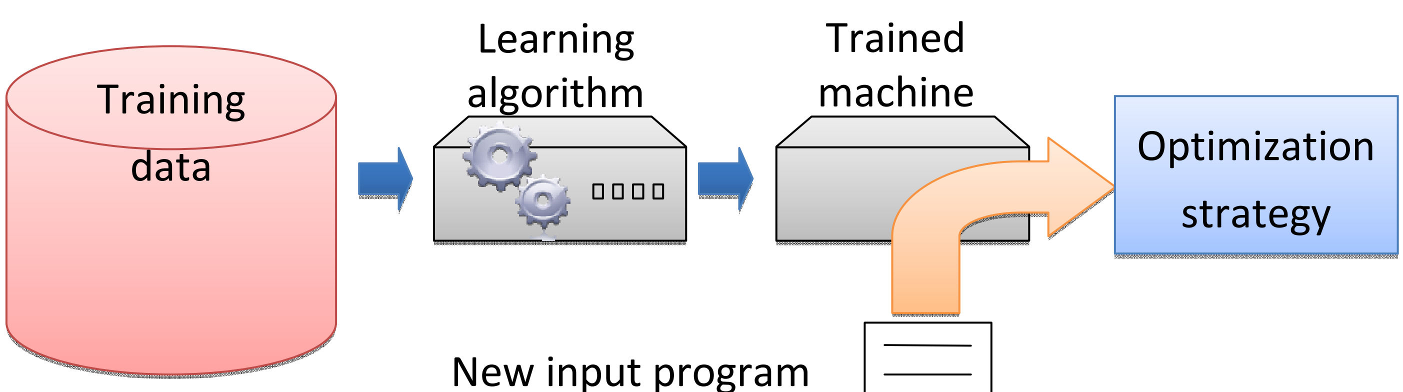
- We propose the empirical model:
  - acquire optimization knowledge by **learning from examples**
  - apply a large number of transformations to benchmark suites to generate code versions
  - measure performance, energy consumption, cost, reliability, etc. for each code version and store in repository
  - describe programs and its regions through **program features**
  - Use machine learning to accurately model the system
  - Deliver the final "trained machine"



Source: I. Guyon "Introduction to ML"

Machine Learning based Optimization

- For each input program, the trained machine is queried to determine effective
  - transformation sequence for each program region
  - parameter setting for runtime environment for a given machine and system status - depends on input data
- Advantages
  - works for changing platforms
  - no hard-wired heuristics that are soon out of date
  - always based on evidence



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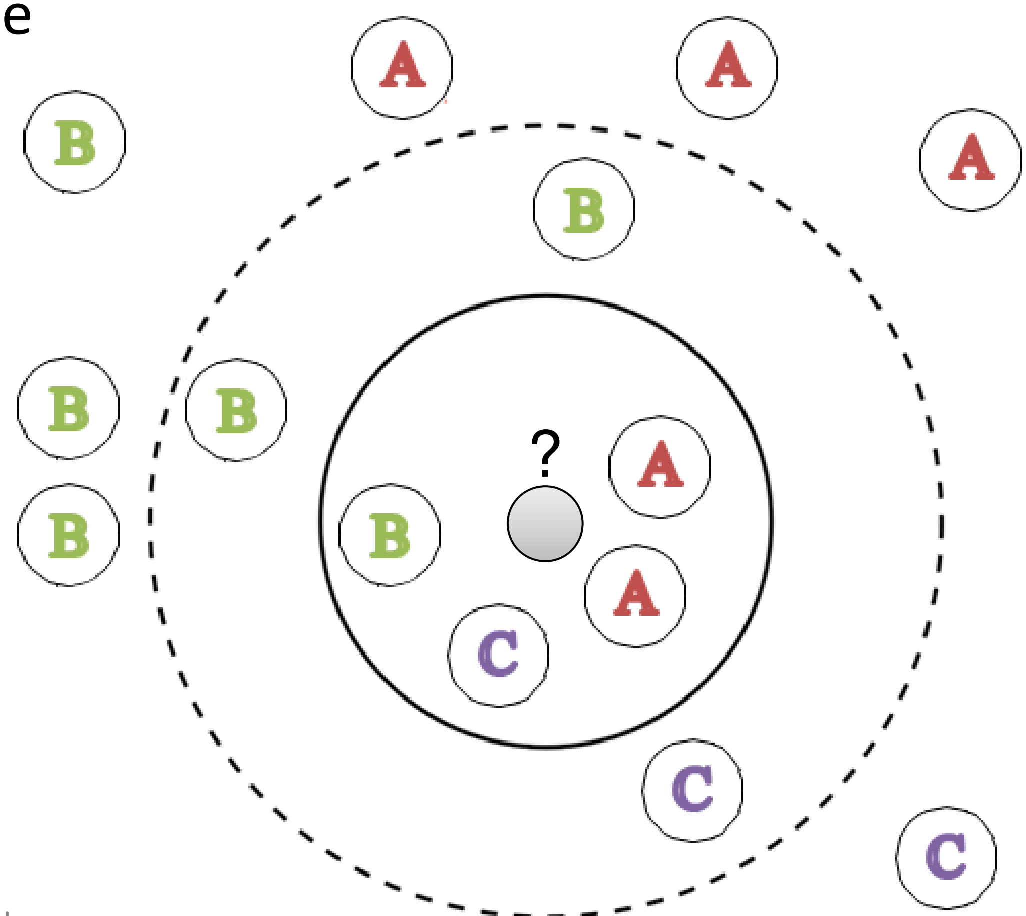
Performance Models to Drive Optimization

- How to describe a parallel programs in a way which is useful for machine learning?
- We need to describe programs in terms of characteristics (program features) that define **similarity,** e.g.: control and data flow information, number of operations, cache misses, communication patterns, volume of data exchanged, …
- Programs with **similar** features are likely to have a similar behavior

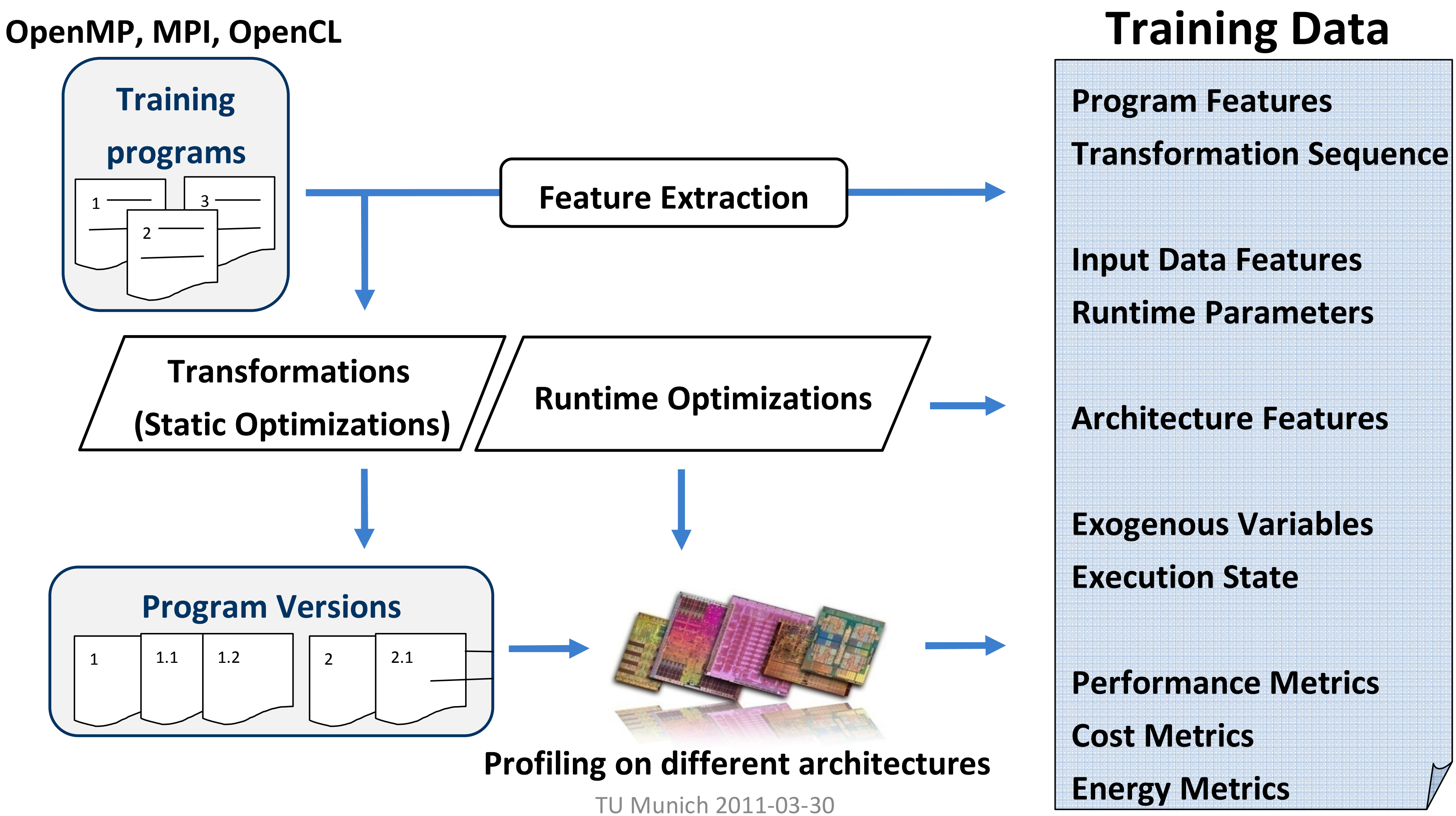
Machine Learning using Nearest Neighbour Classification

k-nearest neighbors algorithm (k-NN):

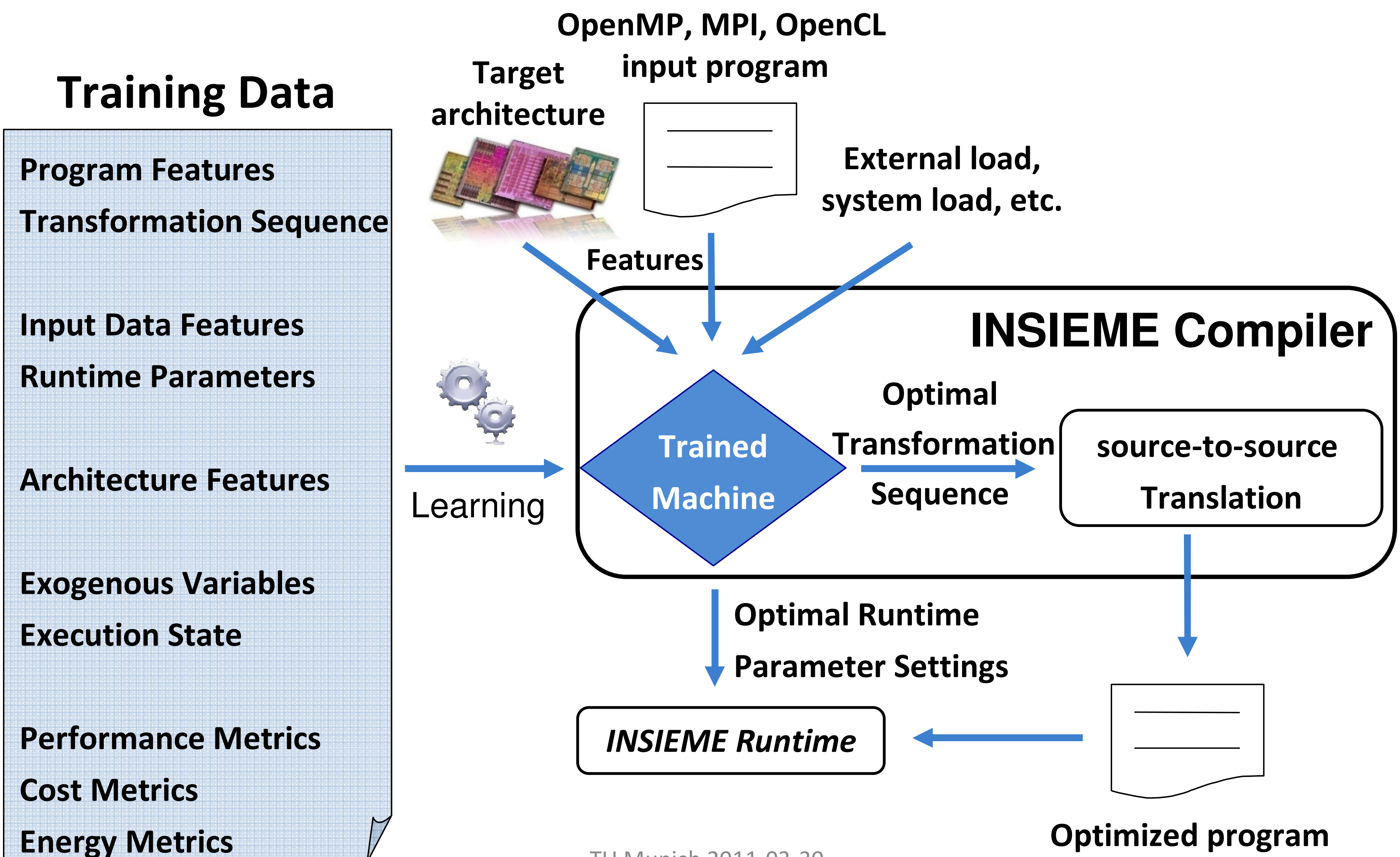
- We need to match our new unseen program to previously seen and recorded programs to determine how to optimize
- Nearest neighbors determines the classification of our new program by measuring the distance in the feature space between the new program and all others
- We predict the new program shares the characteristics of its nearest neighbor



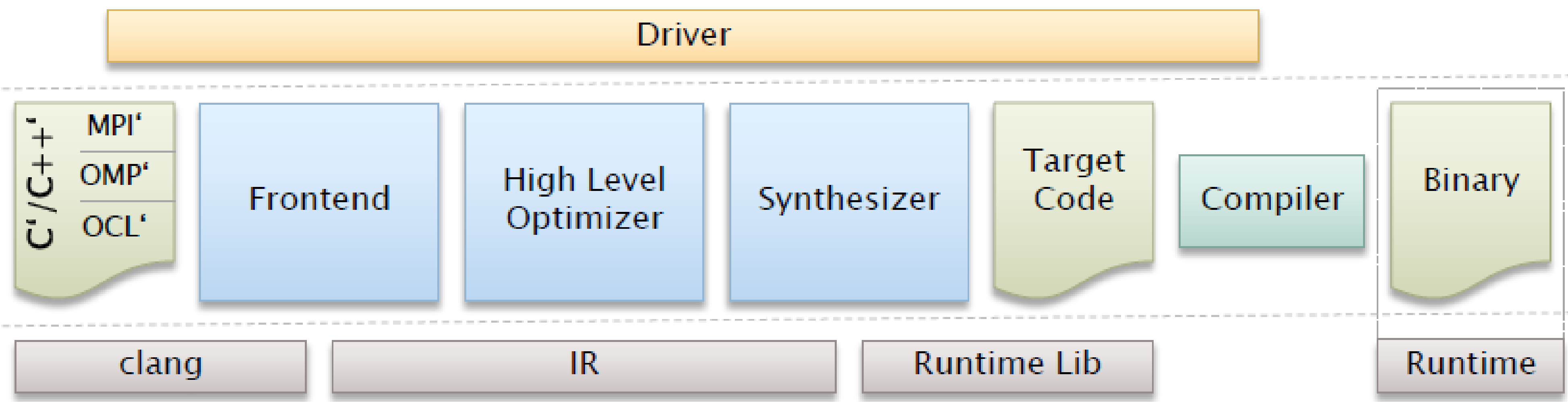
Insieme Training Phase



Insieme Opimization Phase



Insieme Architecture Overview



Insieme Parallel Intermediate Representation - InsPIRe

- Unified Representation of Parallel Programs
  - structural type system
  - closed set of generic types and operators
- Minimal language core
- Explicit Parallelism
- Language level synchronization / communication
- Extendable through composability
- Core module offers
  - data structures to represent programs and annotations
  - manipulation tools

InsPIRe Example

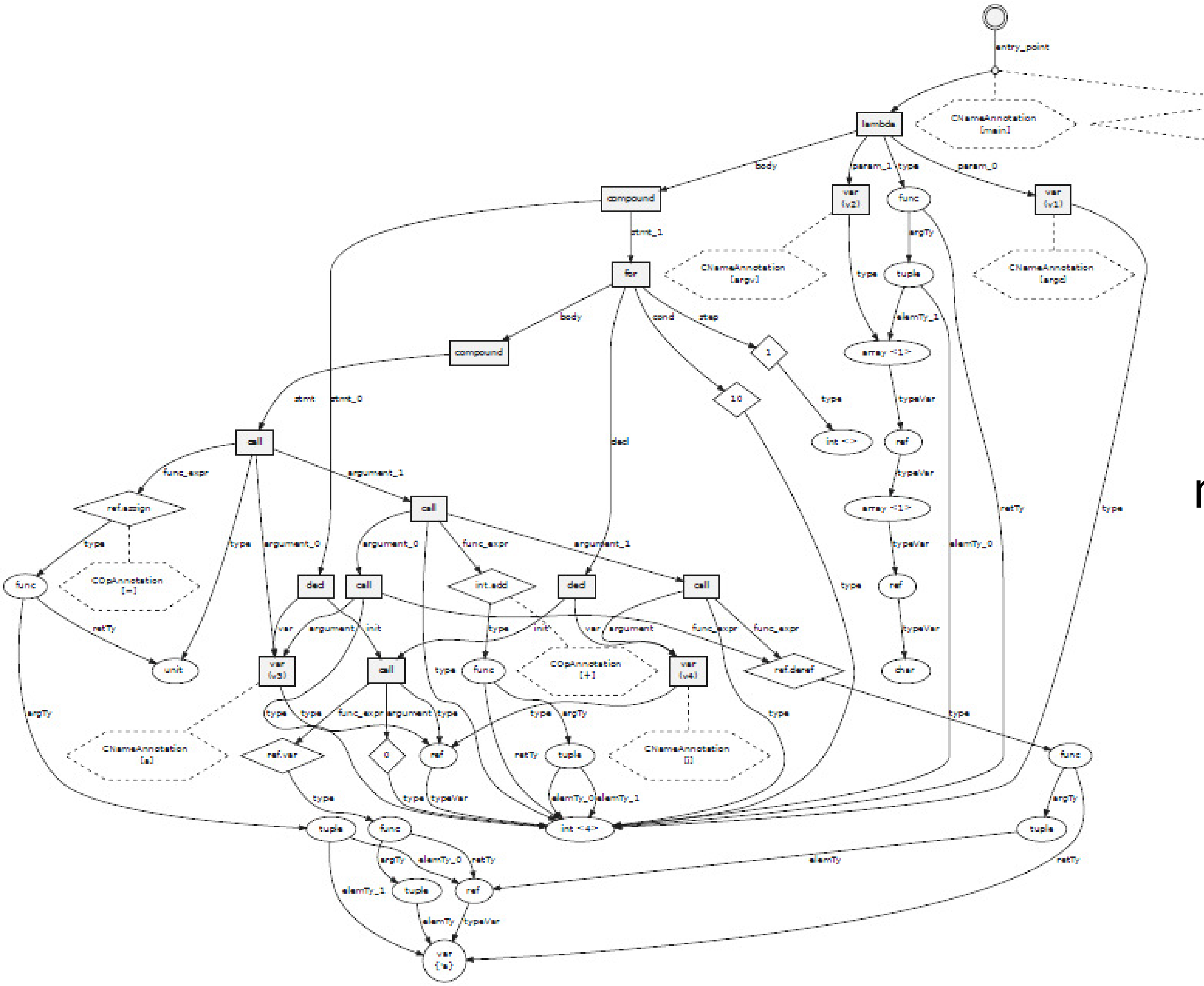
C Input:

```
int main(int argc, char* argv[]) {
   int a;
   for(int i=0; i<10; i++) {
        a += i;
   }
}
```

InsPIRe:

```
fun(int<4> v1, array<ref<array<ref<char>,1>>,1> v2) {
        decl ref<int<4>> v3 =  var(0);
        for(decl ref<int<4>> v4 =  var(0) .. 10 : 1) {
            v3 := v3+v4;
        };
    }
```

InsPIRe Abstract Syntax Tree



Multiple references: 90% memory reduction

XML export/import

Frontend

- Translates input program into InsPIRe - AST
- Capable of supporting hybrid code
- Two steps
  - Step1: C/C++ => IR (syntax)
  - Step2: eliminate MPI / OMP/ OpenCL (semantics)
- `clang` for parsing input (step 1)
- InsPIRe module for manipulations (step 2)

Optimizer

- High Level Transformations
- Pattern recognition
- High-level semantic optimizations
  - e.g. optimized use of arrays/sets/lists exploiting operator semantics
- Loop transformations
- Parallelization / Vectorization
- Integration of high-level knobs
  - e.g. selection of algorithms, data representation

Synthesizer

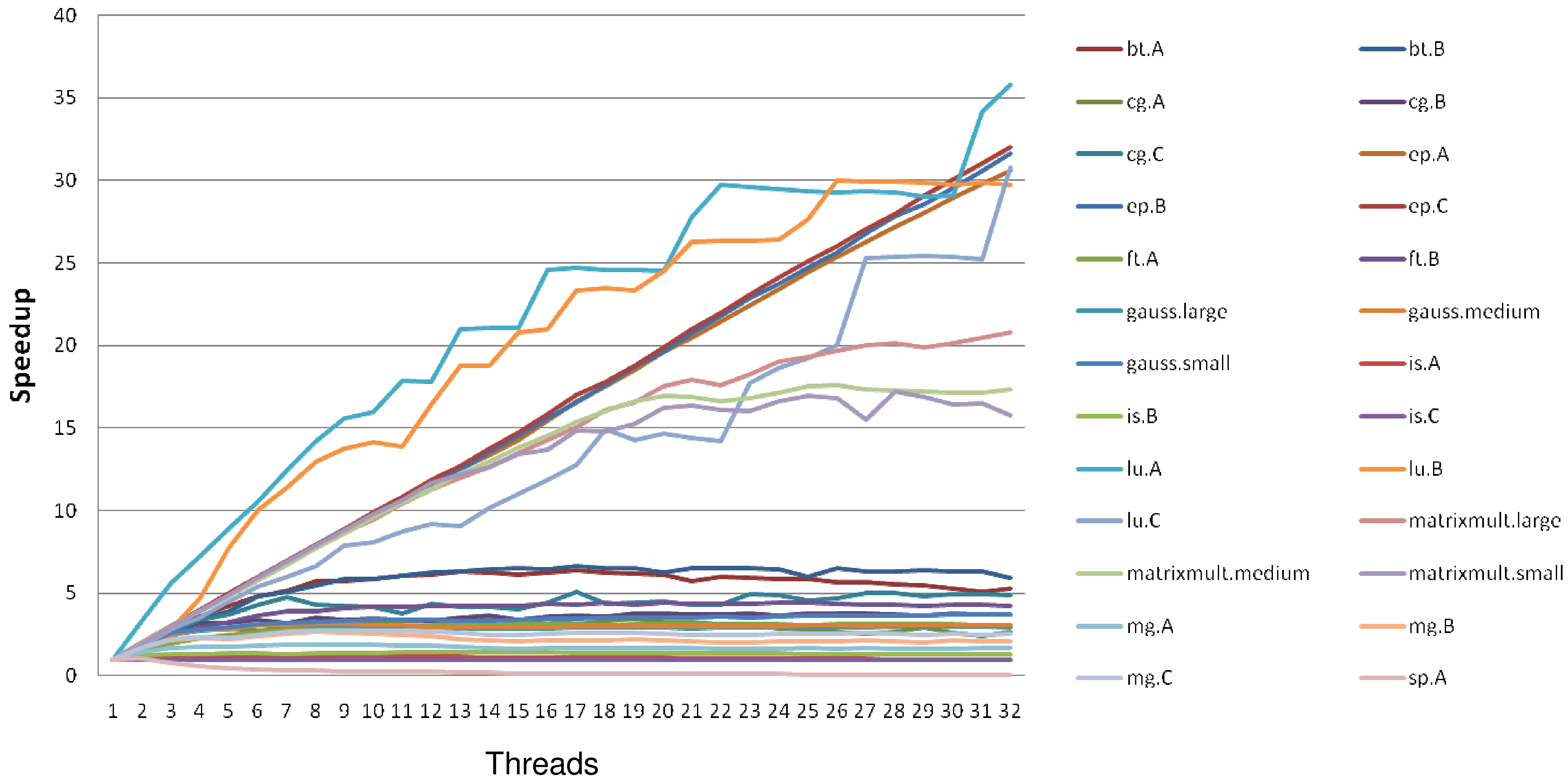
- „Simple“ Backend (first prototype)
- Pure MPI Backend
- Insieme Runtime Backend
- Target specific synthesizers
  - shared memory
  - distributed memory
  - accelerators
  - integration of target specific knobs
  - e.g. scheduling policies, communication protocols, group sizes, thresholds for parallelism

Insieme Runtime

- Runtime Library
  - called by target code
  - target specific extensions (MPI, OpenCL,...)
- Runtime Environment
  - tuning of runtime parameters (knobs)
  - resource management (cores, nodes, accelerators, ...)

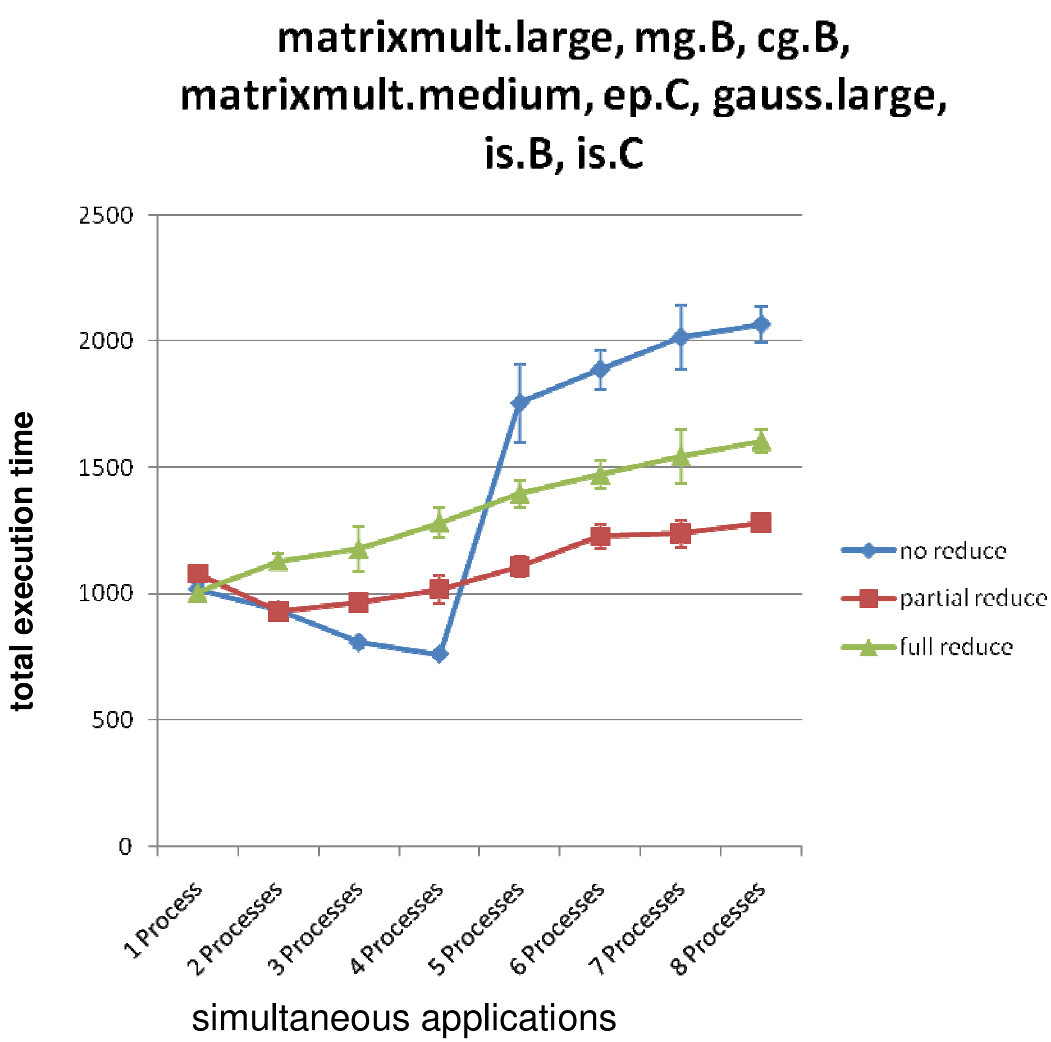
Case Study: OpenMP Benchmarks

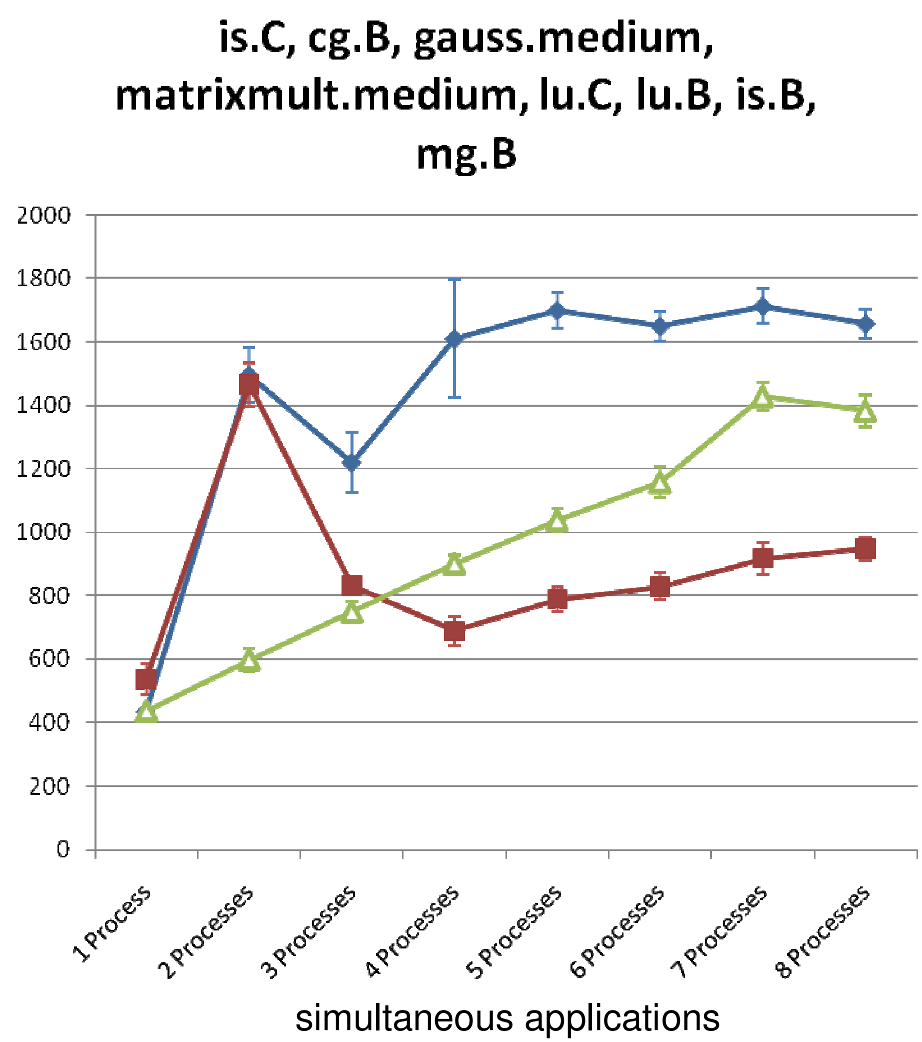
Achievable speedup is limited



Machine: 8 quadcore AMD CPUs (Sun X4600 M2)

Multiple OpenMP applications with different job scheduling strategies

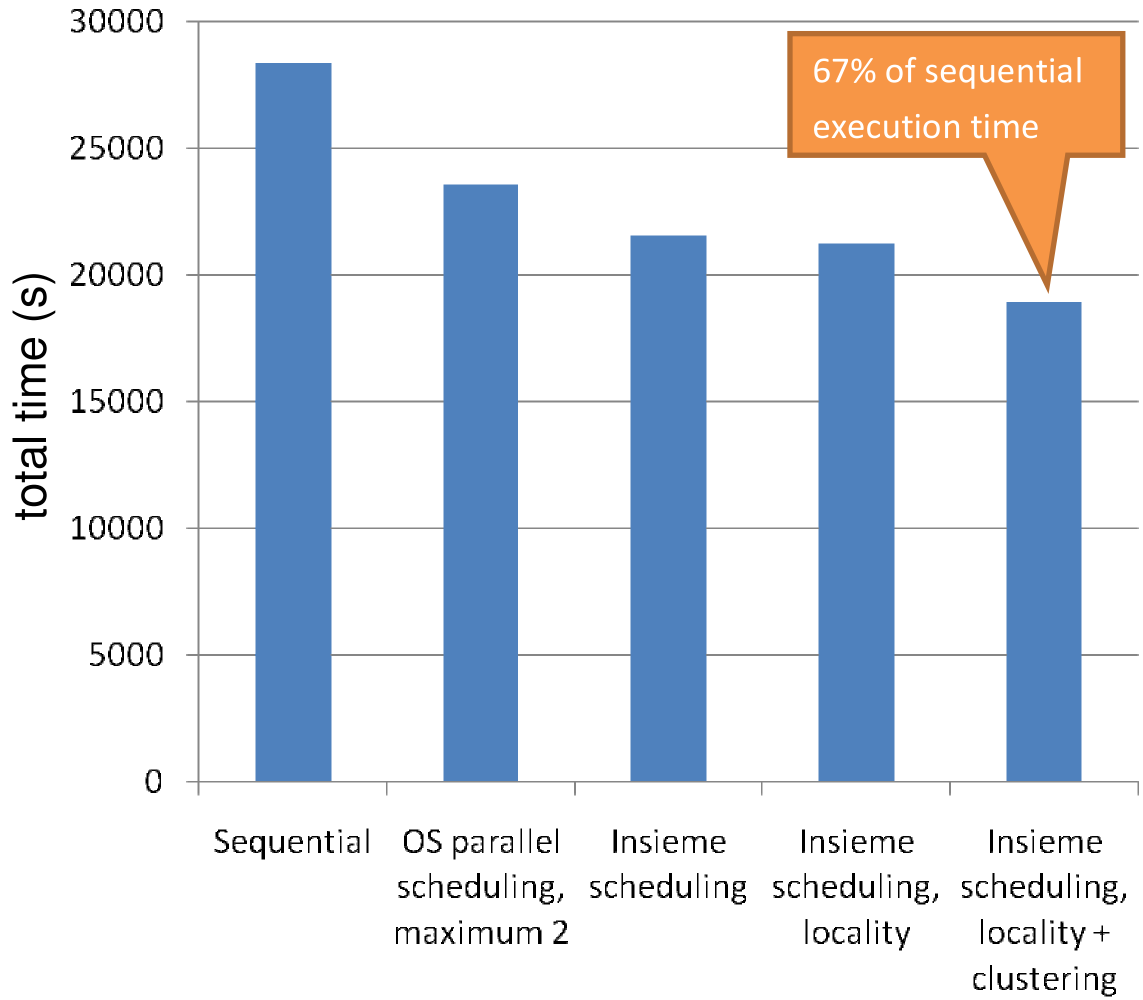




Different strategies of reducing the number of threads assigned to each application

Insieme OpenMP job scheduling

- For each region, optimal thread count is dynamically determined
- Optimization options:
  - locality: increase locality of threads assigned to the same application
  - clustering: clusters of cores should be used by single applications



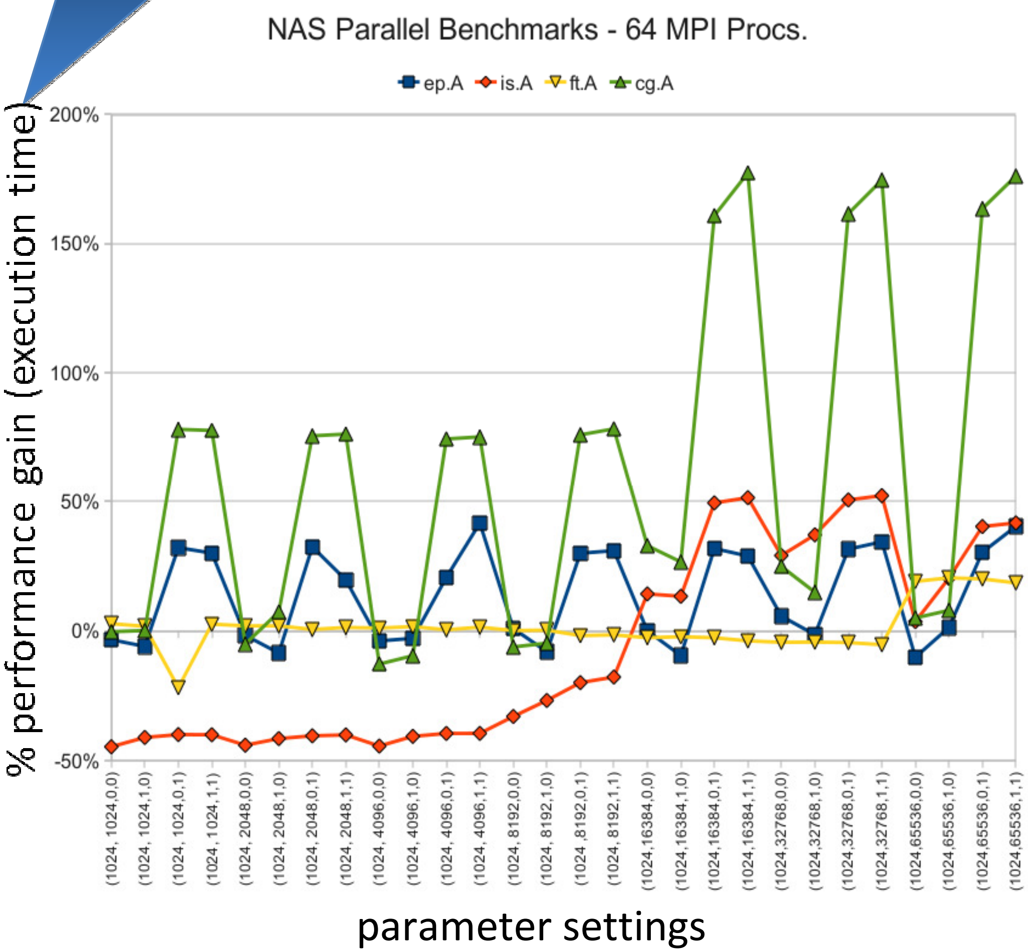
Automatic Tuning of MPI Runtime Parameters

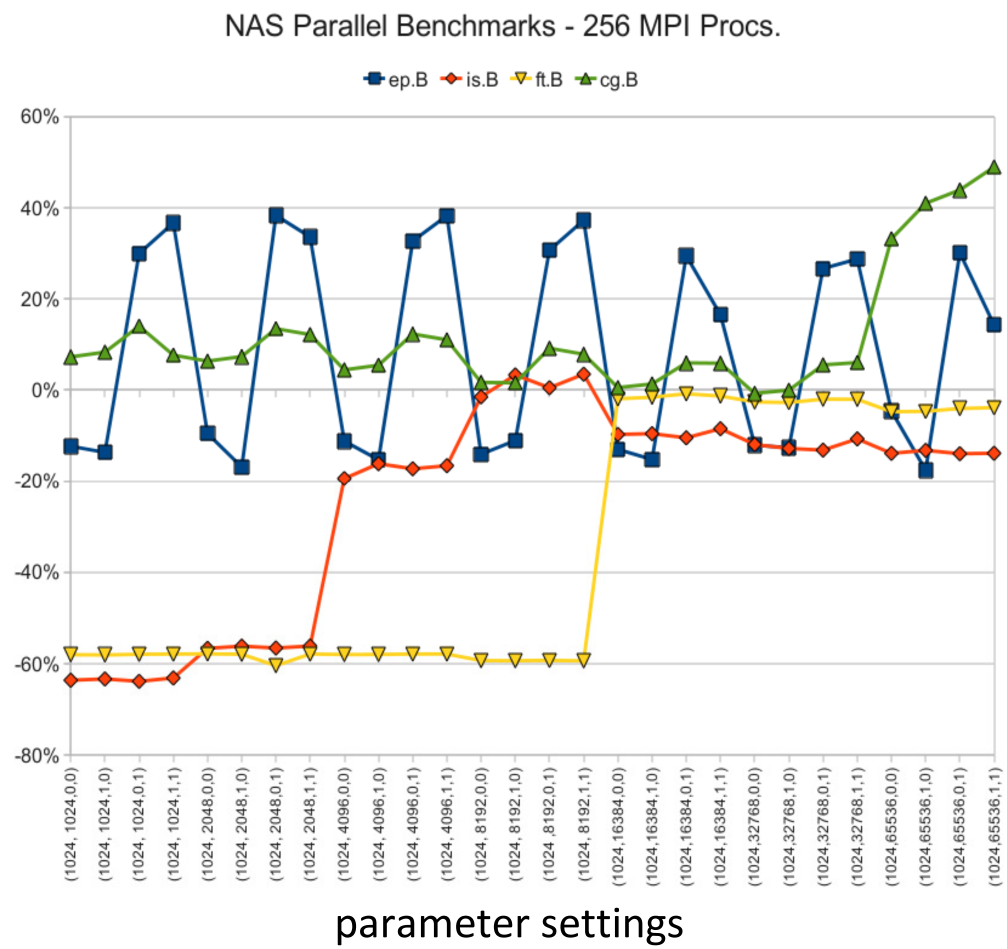
- MPI implementations allow for tuning the runtime environment to better fit the underlying architecture, such as:
  - eager/rendezvous send threshold:
    - use eager or the rendezvous protocol depending on messages size
  - processor affinity flag:
    - bind an MPI process rank to a physical core
- Open MPI's Modular Component Architecture (MCA) provides 100’s of parameters

Effects of MPI Runtime Parameter Tuning

FT, CG, IS and EP from NAS Parallel Benchmarks running on a cluster of SMPs nodes, using 8 vs. 32 nodes

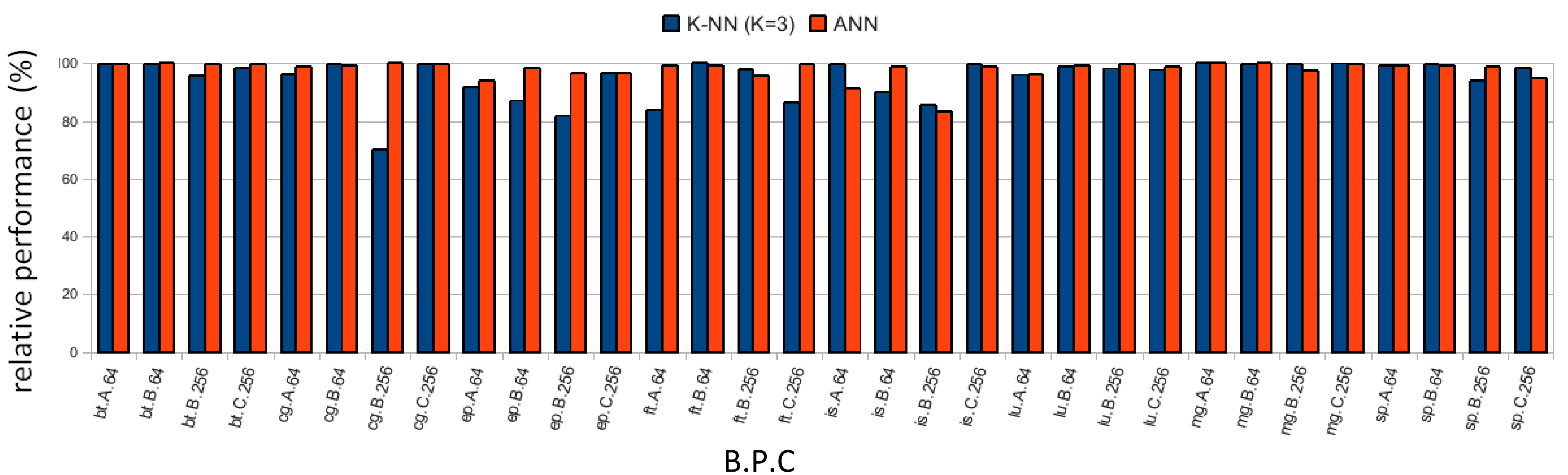
wrt. Open MPI default settings





Using Machine Learning to Predict Optimal Parameter Settings

- Performance of predicted parameter setting, relative to best performance found during exploration, using two learning algorithms:
  - Artificial Neural Network (ANN)
  - K Nearest Neighbors (k-NN)



Summary

- Mult-Language support – MPI, OpenMP, OpenGL - for heterogenous multicore systems
  - Unified parallel intermediate representation
- Analytical aproach not feasible due to complexity
  - Explore optimization space via experiments and machine learning
- Static and Runtime Optimizations
  - Program transformation
  - Tuning of runtime parameters