Palm: Easing the Burden of Analytical Performance Modeling

NATHAN TALLENT, KEVIN BARKER, DARREN KERBYSON, ADOLFY HOISIE

Pacific Northwest National Lab

ISC '15: Performance Modeling: Methods & Applications

July 16, 2015

Analytical Modeling of Performance is Hard

- Analytical model of performance
  - Quantitatively explains and predicts application execution time

  - Diagnose performance-limiting resources, design machines, etc.
- How is application modeling difficult?
  - Modeling requires expertise and labor
    - model critical path: identify parameters for each critical path segment
    - parameter reduction: represent ‘invariant’ code as measurement
    - validate: iterate until model captures all interesting behavior
  - Representing, reproducing and distributing models is ad hoc
    - 1 modeler, N application variants
    - 1 application, N modelers

What can a tool automate? Can we pair model and source code?

Palm: How Can Tools Help?

- Identify and formalize best practices
- Make the simple easy and the difficult possible
  - Provide a fully general framework (do not hinder)
  - Automate routine tasks
- Facilitate a divide-and-conquer modeling strategy
  - Construct model by composing sub-models
  - Define model structure from static & dynamic code structure
- Assist reproducibility
  - Generate same model given same input
  - Generate model according to well-defined rules
- Assist validation (feedback loop)
  - Generate contribution and error reports

Palm: Performance & Architecture Lab Modeling Tool

Outline

- Overview
- Scientific Workflows and Resource Contention
- Silicon Photonics’ Potential For Graph Applications

Palm: PAL Modeling Tool

N. Tallent & A. Hoisie. ICS 2014

annotated source
Palm Compiler
reference & instrumented executables
static analysis
Palm Monitor
profiles
Palm Generator

- Annotations guide modeling and express insight
  - Develop model and application in tandem
  - Decompose modeling task into sub-problems
  - Reasonable because applications change slowly
- Generate model from (static/dynamic) annotation structure
  - Combine annotation expressions and measurements
- Models are 'first class' objects
- Generate same model given same input (reproducible)
- Generated model is an executable program
  - Instantiate with parameters to generate prediction

parameters
model (program)
prediction & diagnostics
refine as necessary

Simple Annotations for Nekbone (CG solver)

```
program nekbone
  !$pal model init
  call init_dim, call init_mesh, …

  !$pal model cg
  call cg(…)
end
```

model: classify code block and model one instance of its execution; if expression is omitted, automatically synthesize one

```
subroutine cg(…)
  !$pal loop n_cg = ${n_iter}
  do iter=1,n_iter
     …
  enddo
```

loop: model several instances of a code block; name block and model its trip count

def: define model variable or function

${x}: program value reference: capture x's value during program execution and compute statistic across instances & ranks

```
void halo_exchange(buf[n], n…)
  #pragma pal loop n_send = ${n}[max]
  for(i = 0; I < n; ++i)
     isend(…, buf[i]…);
```

```
#pal def snd(sz) = …
```

```
void isend(…size_t n, uint dst…)
  #pal model send = snd(${n})
  MPI_Isend(… n, dst…)
```

Palm's Model Matches Human-Generated Model

```
class Model
    def nekbone() (init() + cg() + k₂) end

    def init() k₁ end

    def cg()
        n_cg * (f() + reduce₁() + … + reduce₃() +
                26 * send())
    end

    def snd(sz) @machine.send(sz) end
end

require 'machine-pic.rb'
m = Model.new(PAL::ExecutionPIC.new(…))
m.eval(parameter-list)
```

A model is a program. Here, it is a Ruby script.

synthesized model function (from model & loop annotations and measurements)

cg() model's form matches a human-generated model: $T_f + 3\ T_{reduce} + 26\ T_{send}$

model function (from def annotation)

machine parameters (from model library)

evaluate to obtain runtime

Palm: Using Models

annotated source → Palm Compiler → reference & instrumented executables → Palm Monitor → profiles → Palm Generator

Palm Compiler → static analysis → Palm Generator

Palm Generator → model (program) → prediction & diagnostics

parameters → model (program)

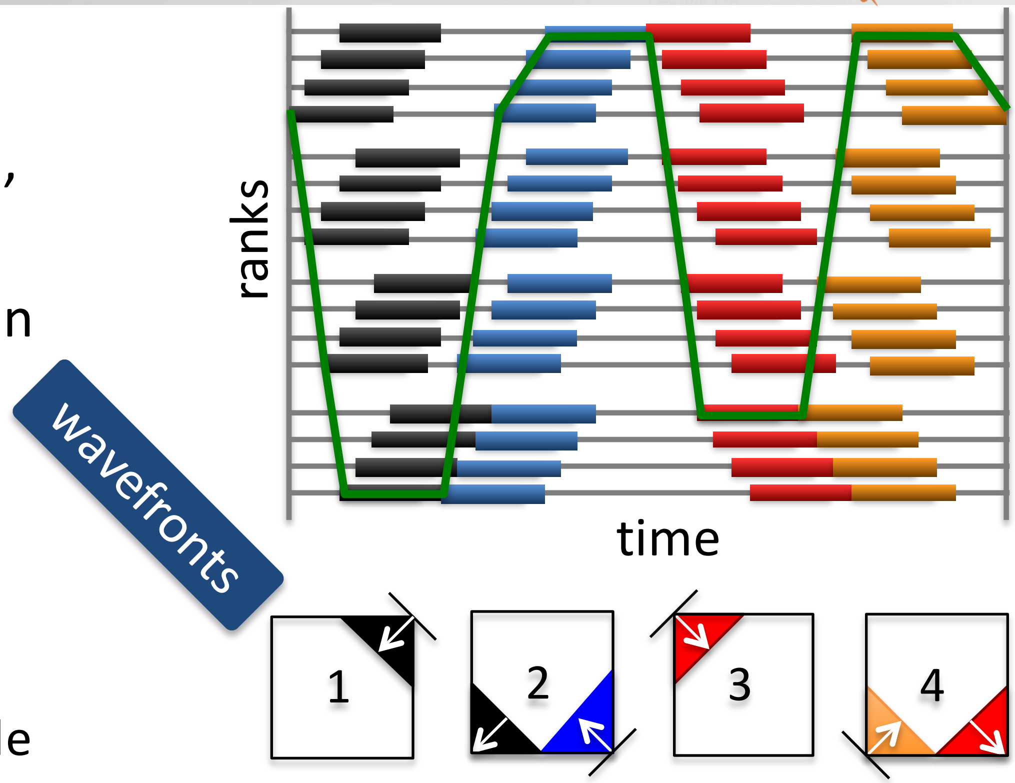
- Models are (Ruby) programs
  - scripting language is convenient; could use machine code
  - invoke by passing appropriate parameters (e.g., # cores)
  - replace sub-models by re-defining functions
- Refine annotations using model diagnostics
  - show contribution of each sub-model (expression)
    - quantitatively distinguish 1st- and 2nd-order effects
  - show errors of each sub-model w.r.t. measurements
    - understand effects of replacing a sub-model (function)
    - example: new communication model

refine as necessary

Modeling a Wavefront Application: Sweep3D

- Sweep3D: 2D pipeline
  - Wavefronts propagate in phases, yielding active and idle states
  - Idle (& pipeline) time depends on ranks, phase, & pipeline stage

M(rank, phase, stage)



- Need more than static analysis
  - pipeline formed dynamically
    - state variables and guarded code
- Palm assists modeling the critical path – before it exists
  - express idle time as function of a pipeline stage's model
    - model critical path using a forward reference to a generated model
  - Palm assembles model using dynamic analysis & composition rules

M(rank, phase, *M*(stage)) → *M*(rank, phase)

human

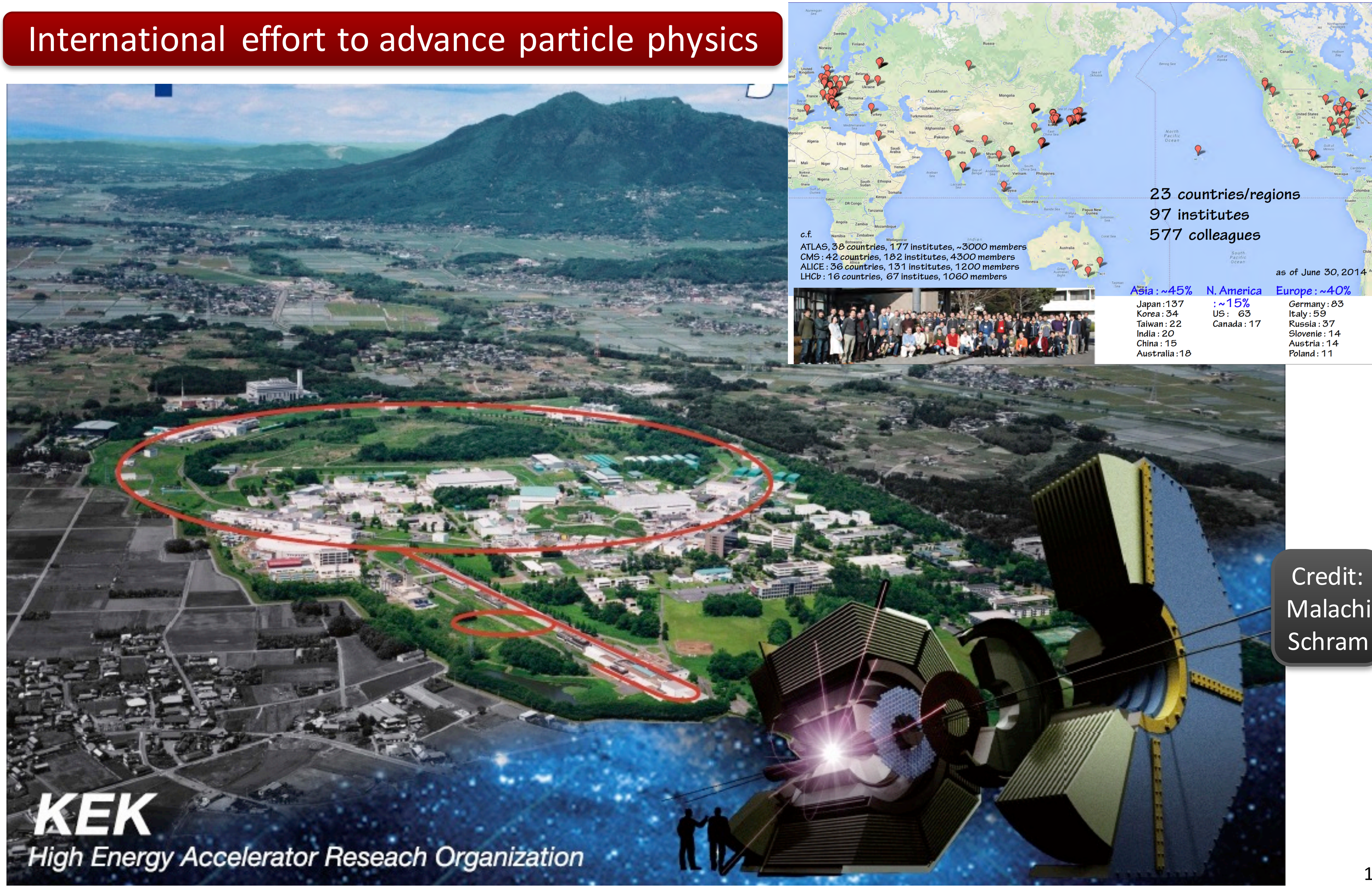
tool

Outline

- Overview
- Scientific Workflows and Resource Contention
- Silicon Photonics’ Potential For Graph Applications

High Energy Physics: Belle II

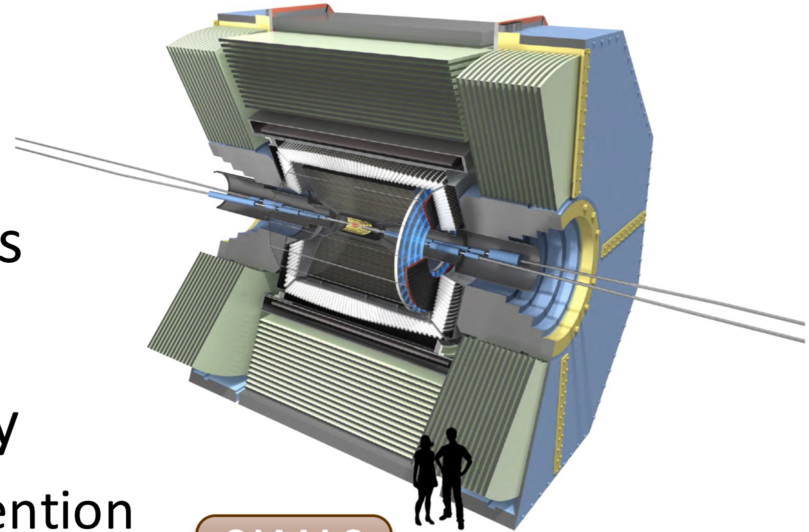
International effort to advance particle physics

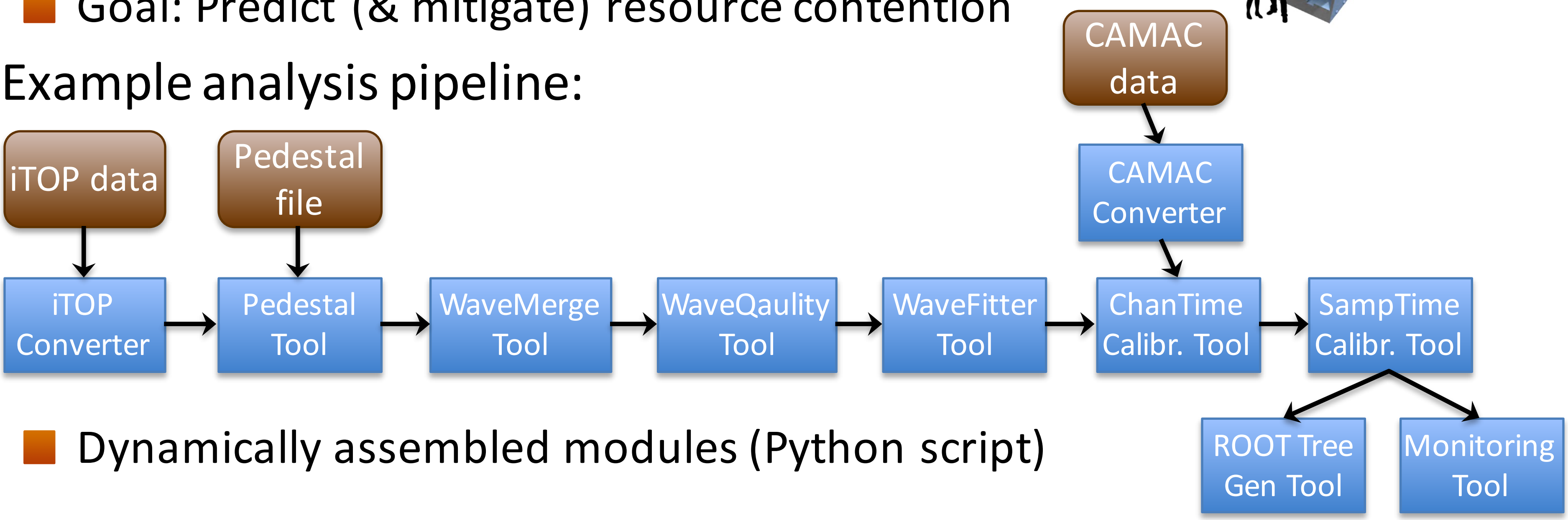


Credit: Malachi Schram

Belle II Experiments Require Extensive Analysis

- Data! 25 PB/year of raw data
  - Stored data expected to reach 350 PB
- Belle II Workflow: Extensive data analysis
  - Normalize data and 'do physics'
- Many analysis pipelines run concurrently
  - Goal: Predict (& mitigate) resource contention
- Example analysis pipeline:





  - Dynamically assembled modules (Python script)

Palm creates workflow model by composing models for each module

Outline

- Overview
- Scientific Workflows and Resource Contention
- Silicon Photonics' Potential For Graph Applications

Assessing the Impact of Silicon Photonics

- Question: What is the impact of silicon photonics on graph-based workloads in the 4–6 year timeframe?
- Methodology
  - Work with architects; Identify silicon-photonics enabled systems
    - IBM TOPS (64 nodes, fully connected): photonics off node
    - Oracle Macronode (32 nodes, fully connected): photonics on & off node
  - Draw workloads from PNNL's experience with graph applications
  - Compare silicon-photonics systems with electrical counterpart
    - fix footprint; fix power
  - Large, distributed graphs ("require a rank")
    - Validate at scale 34; Project at scale 40
    - Scale $\stackrel{\text{def}}{=}$ $\log_2$(edges)
  - Models explore both performance and power
  - Model intra-node and inter-node data movement

Two Workloads To Represent Important Use Cases

Community Detection

- Input: Graph with weighted edges
- Output: Disjoint sets of related vertices
- Aggregated personalized all-to-all to send each edge's target info (~1 GB)
- Iterate until Δ-modularity < threshold
  - Each vertex initially its own community
  - For each vertex, determine whether modularity increases by moving to neighboring community

Large, aggregated messages

- Optimized for cluster networks
- Combine reqs with same target vertex

More computation

- Modularity requires collectives
- Denser graph; aggregation cost

Matching (½ approx)

- Input: Graph with weighted edges
- Output: Maximal weighted matching
- Two phases b/c of multi-step protocol
  - Based on locally dominant neighbor
- Phase 1:
  - Try matching each vertex
  - Aggregate messages between nodes
- Phase 2:
  - Try matching on "matched frontier"
  - Iterate until all vertices are matched
  - Use very small (24 B) messages

Small messages

Scale-40 distributed graphs

Two Workloads To Represent Important Use Cases

Community Detection

- Input: Graph with weighted edges
- Output: Disjoint sets of related vertices
- Aggregated personalized all-to-all to send each edge's target info (~1 GB)

- Iterate until Δ-modularity < threshold
  - Each vertex initially its own community
  - For each vertex, determine whether modularity increases by moving to neighboring community

Large, aggregated messages

- Optimized for cluster networks
- Combine reqs with same target vertex

More computation

- Modularity requires collectives
- Denser graph; aggregation cost

Using Palm…

Annotations convey insight about input graph

Capture important runtime properties. E.g.: probability that communities are formed

Swap network models

Convenient representation

Challenge: Help specialize model for graph input class

Conclusions

- Ease burden of modeling
  - Facilitate divide-and-conquer modeling strategy
  - Automatically incorporate measurements
  - Generate contribution and error reports
- Enable first-class models
  - Coordinate models and source code
  - Functions unify annotations, generated models, and measurements
- Expressive: elegantly represent non-trivial critical paths
  - Annotations provide convenience within fully generic framework
- Reproducible: generate same model given same input
  - Generate model according to well-defined rules
  - Define model structure from static & dynamic code structure
- Future: Especially interested in more dynamic assistance