$$\vec{a} = \frac{d\vec{v}}{dt}$$

(Nearly everything you need to know about) optimising convolutional neural networks on embedded platforms with OpenCL

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Example: trends and challenges in auto industry

Trends

- Connected cars
- Natural user interfaces
- Autonomous and semi-autonomous cars

Challenges

- Sophisticated algorithms
- Heterogeneous hardware
- Software must be both reliable and efficient

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Convolutional neural networks (CNNs)

- “Deep” (multi-layered) neural networks:
  - One or more convolutional layers
  - One or more fully connected layers
  - Normalisation, pooling, dropout...
- Take advantage of the 2D structure in images, hence useful for classification, localisation, detection.

CNN example: AlexNet (A. Krizhevsky et al., 2012)

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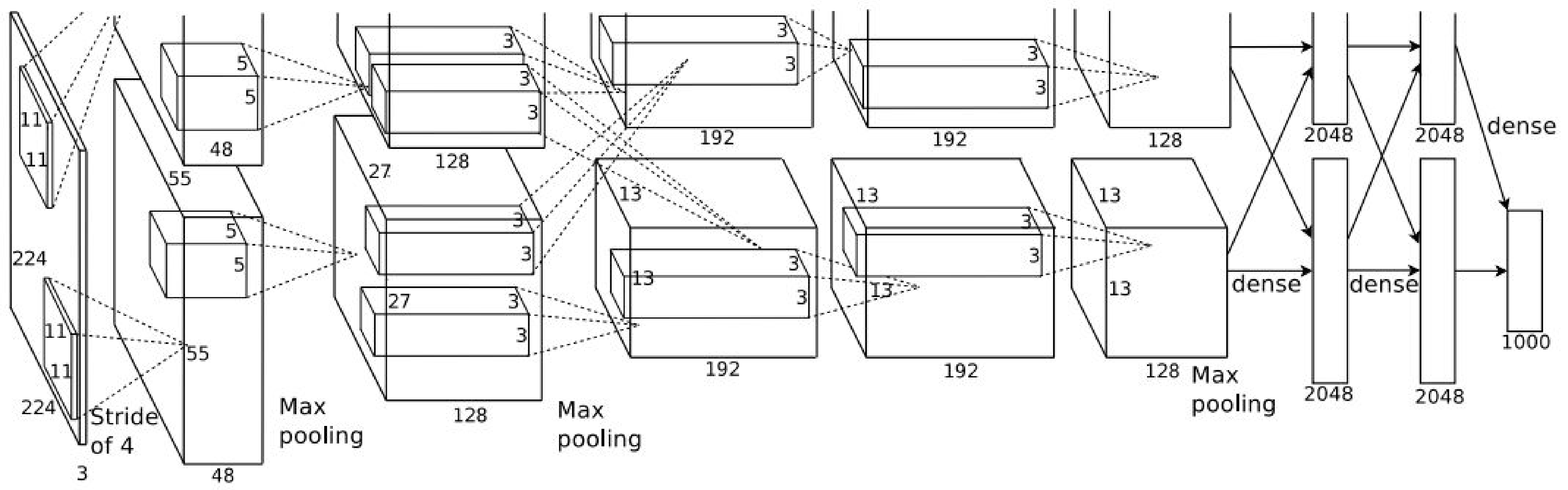

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CNN training and deployment

- Training is typically done on clusters with NVIDIA GPUs.
- Deployment is spreading to mobile & embedded platforms.
    - Can we deploy a CNN to achieve the required rate and accuracy of recognition on a given platform?
    - Can we identify or build such a platform under given constraints such as those on power, memory, price?
    - If all else fails, can we design another CNN by trading off performance, accuracy and cost?

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Optimising CNNs with OpenCL

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OpenCL support in Caffe

- Caffe (caffe.berkeleyvision.org) is a popular deep learning framework with a DSL for describing neural networks.
- Caffe's master branch still only supports CUDA.
- AMD's Caffe port uses OpenCL 1.2 and C++ templates.
- Caffe's OpenCL branch is in active development led by Fabian Tschopp.
  - ViennaCL: required.
  - clBLAS: optional.

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Preliminary results for AlexNet on Chromebook 2

- Samsung Chromebook 2:
  - Quad-core ARM Cortex-A15 CPU @ 1900 MHz
  - Quad-core ARM Mali-T628 GPU @ 533 MHz
  - 2 GB RAM
- AlexNet w/ batch size of 128 using:
  - CPU w/ OpenBLAS 0.2.17
  - GPU w/ ViennaCL 1.7.1: ~10x slower than OpenBLAS
  - GPU w/ clBLAS 2.4: ~4x slower than OpenBLAS

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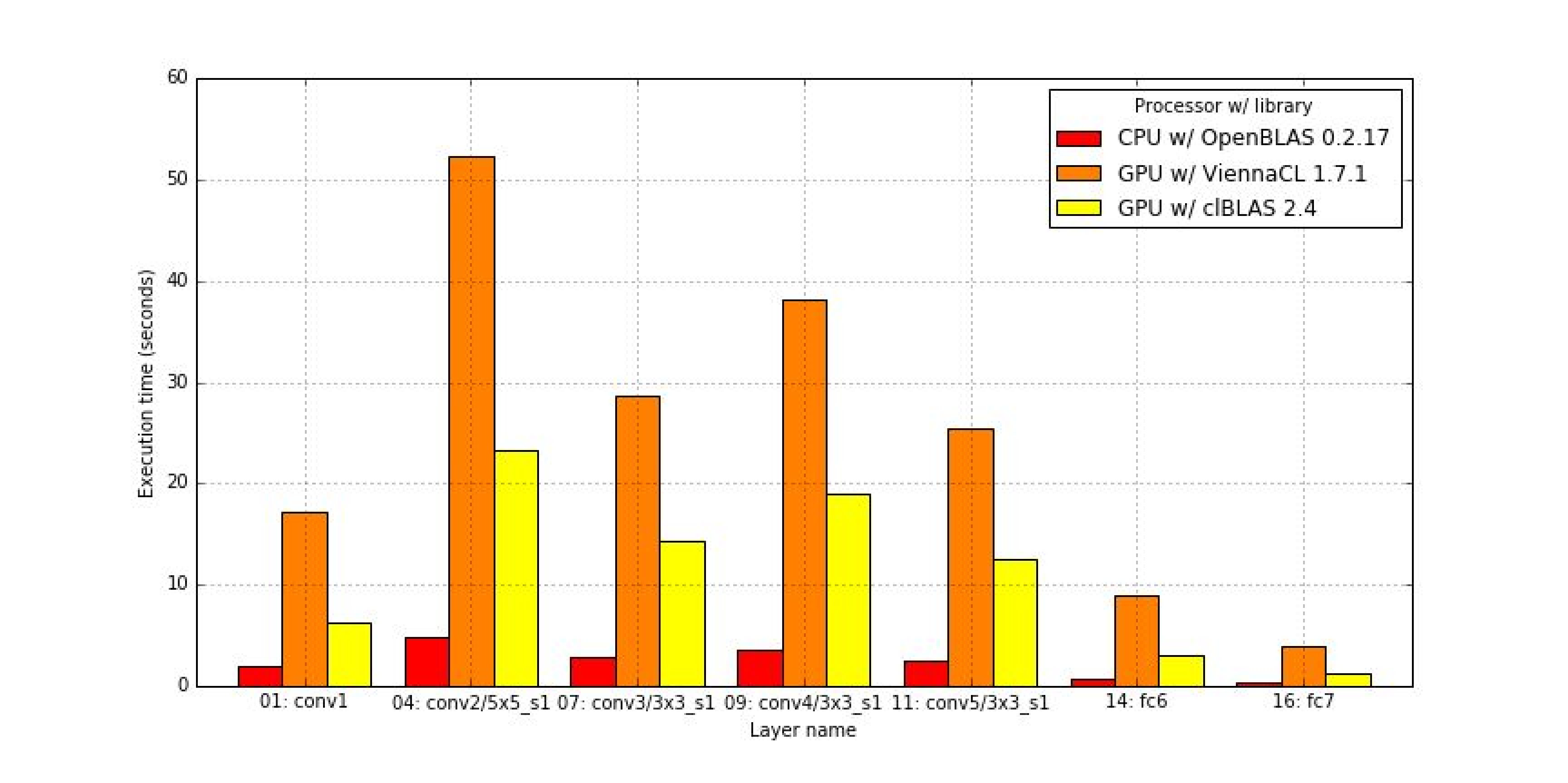

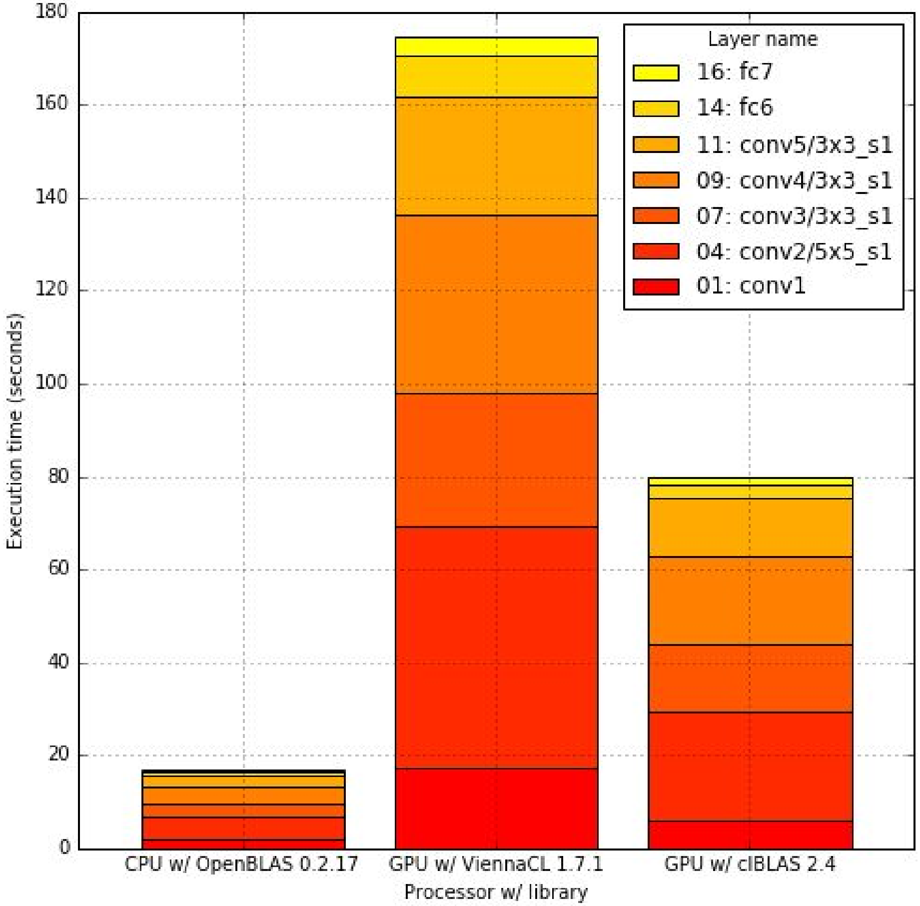

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SGEMM - FP32 matrix-matrix multiplication

- Convolution is implemented as matrix-matrix multiplication.
- ~20,000 kernel enqueues, ~95% of which do SGEMM.
- Pros:
  - Single, regular routine to optimise.
- Cons:
  - Memory expansion (size + bandwidth implications).
  - Possibly awkward dimensions.
  - Is FP32 really necessary?

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Crowdtuning ARM’s GEMM implementation

- ViennaCL performs FP32 GEMM @ <0.5 GFLOPS
- ARM’s implementation performs:
  - FP32 GEMM @ ~24 GFLOPS
  - FP16 GEMM @ ~45 GFLOPS
  - FP32/FP16 GEMM @ ~27 GFLOPS

cknowledge.org/repo/web.php?wcid=graph:crowdtune-sgemm-mali

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Open call for collaborative optimisation

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Collaborative optimisation of CNNs

Huge design and optimisation space

- Network design (state-of-the-art is ad-hoc).
- Network “compression” (50x storage reduction; 1% accuracy loss).
- Basic building blocks (GEMM, direct convolutions, FFT?).
- Data types (FP32, FP16, INT8?) + data layout transformations.

Continuous benchmarking and optimisation (see next slide)

- For speed, accuracy, size, energy consumption, etc.
- Across representative inputs, filter sizes, hardware platforms, etc.

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Collective Knowledge: our humble solution

- Open framework + methodology (github.com/ctuning/ck).
- Combines reproducible experimentation with predictive analytics to extract “valuable insights” from “raw data”.
- Stimulates collaboration, thus reduces costs and risks.
- Dramatically accelerates knowledge discovery and optimization from many months to few days.
- cknowledge.org; bit.ly/ck-date16; bit.ly/ck-multiprog16; arxiv.org/abs/1506.06256; dx.doi.org/10.3233/SPR-140396

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Open call for collaborative benchmarking

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The need for representative workloads

Benchmark [bench-mahrk]

- *noun* an abusive term for poorly constructed software, e.g. “this piece of software is a benchmark”
- *verb* to create a meaningless set of measurements, e.g. “we benchmarked the latest device”

Workload [wurk-lohd]

- *noun* a self-contained series of machine-executable actions formed from production code that presents a use case of interest for performance analysis

-- “Benchmarks vs Zombie Apocalypse: a Comparison”

(ADAPT’16 keynote by Ed Plowman, ARM)

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The need for collaborative design and optimization

- Ever increasing complexity (many things may go wrong).
- Large, diverse engineering groups (e.g. hardware designers, system programmers, performance analysts).
- Ineffective collaboration wastes precious resources and increases business risks.
- Users run tomorrow’s workloads on yesterday’s hardware.
- Too easy to ignore emerging workloads, as they simply do not have the same status as benchmarks.

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Community-sourced workloads

- Incentives for academia: demonstrable impact.
- Incentives for industry:
  - Software developers: similar to open-source software.
  - Hardware vendors:
    - Focussed effort on better design and optimisation.
    - Reduced effort on benchmarks.
    - Fair competition.

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Our long term mission is to enable efficient and reliable computing everywhere.

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Thank you!

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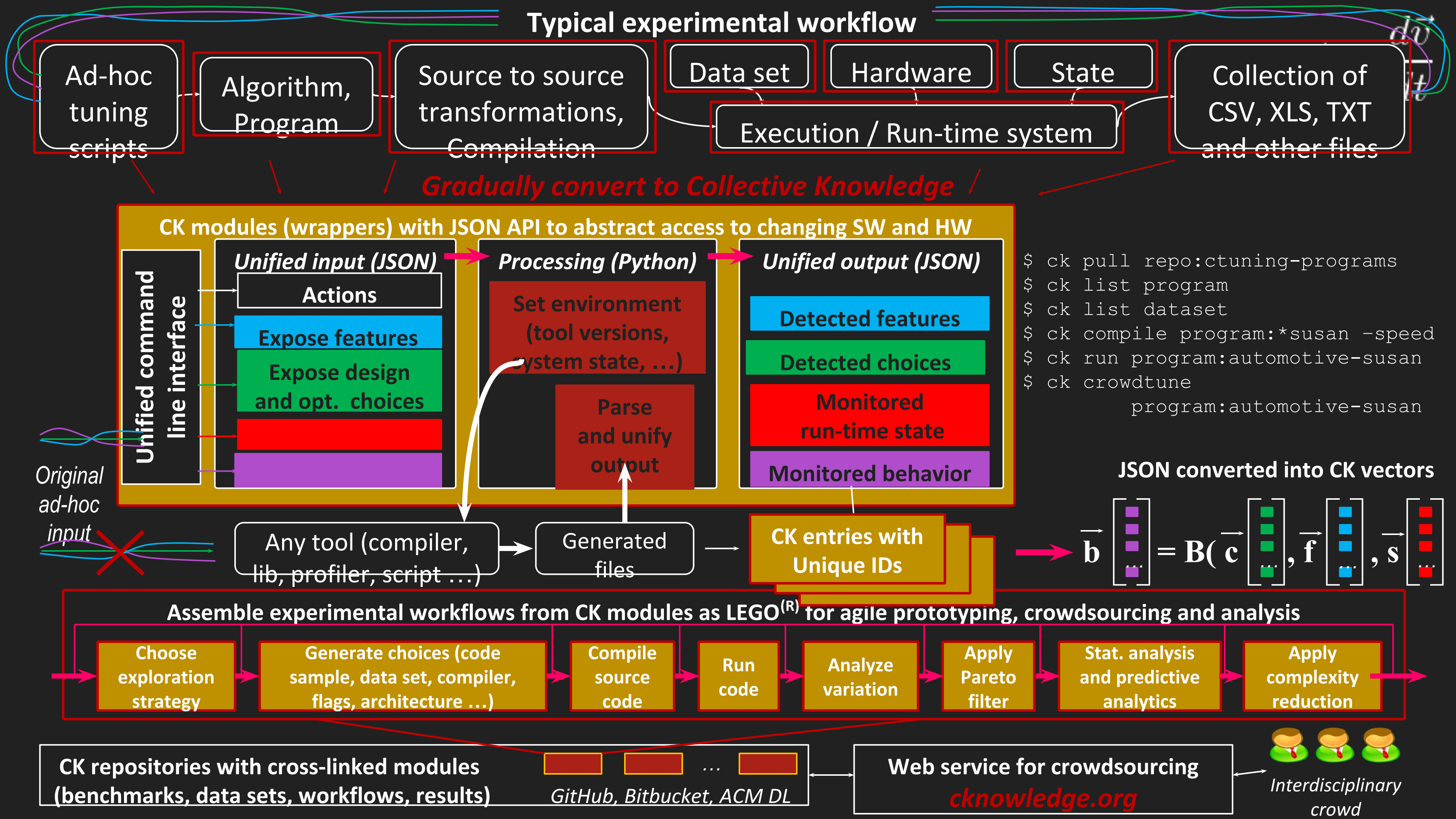
Typical experimental workflow
Ad-hoc tuning scripts
Algorithm, Program
Source to source transformations, Compilation
Data set
Hardware
State
Execution / Run-time system
Collection of CSV, XLS, TXT and other files
Gradually convert to Collective Knowledge
CK modules (wrappers) with JSON API to abstract access to changing SW and HW
Unified command line interface
Unified input (JSON)
Actions
Expose features
Expose design and opt. choices
Processing (Python)
Set environment (tool versions, system state, …)
Parse and unify output
Unified output (JSON)
Detected features
Detected choices
Monitored run-time state
Monitored behavior
$ ck pull repo:ctuning-programs
$ ck list program
$ ck list dataset
$ ck compile program:*susan –speed
$ ck run program:automotive-susan
$ ck crowdtune
program:automotive-susan
Original ad-hoc input
Any tool (compiler, lib, profiler, script …)
Generated files
CK entries with Unique IDs
JSON converted into CK vectors
b = B(c , f , s
Assemble experimental workflows from CK modules as LEGO(R) for agile prototyping, crowdsourcing and analysis
Choose exploration strategy
Generate choices (code sample, data set, compiler, flags, architecture …)
Compile source code
Run code
Analyze variation
Apply Pareto filter
Stat. analysis and predictive analytics
Apply complexity reduction
CK repositories with cross-linked modules (benchmarks, data sets, workflows, results)
…
GitHub, Bitbucket, ACM DL
Web service for crowdsourcing
cknowledge.org
Interdisciplinary crowd

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Acknowledgements

HiPEAC

CARP (FP7)

MILEPOST (FP6)

TETRACOM (FP7)