Enabling open and reproducible research at computer systems conferences

the good, the bad and the ugly

cTuning.org/ae

fursin.net/research

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CNRS webinar
Grenoble
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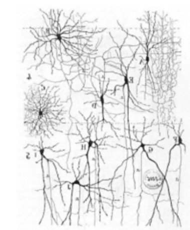
Seminar outline

- **What is computer systems research?**
- **Major problems in computer systems' research in the past 15 years**
- **Artifact Evaluation Initiative**
  - **Good:** active community participation with ACM/industrial support
  - **Bad:** software and hardware chaos; highly stochastic behaviour
  - **Ugly:** ad-hoc, non-portable scripts difficult to customize and reuse
- **Improving Artifact Evaluation**
  - Preparing common replication/reproducibility methodology (new ACM taskforce on reproducibility)
  - Introducing community-driven artifact and paper reviewing
  - Introducing common workflow framework (Collective Knowledge)
  - Introducing simple JSON API and meta for artifacts
  - Introducing portable and customizable package manager
- **Demonstrating open and reproducible computer systems' research**
  - Collaboratively optimizing deep learning across diverse datasets/SW/HW
- **Conclusions and call for action!**

Back to basics: what is computer systems' research?

Users of computer systems (researchers, engineers, entrepreneurs) want to quickly prototype their algorithms or develop efficient, reliable and cheap products



Computer System

Result

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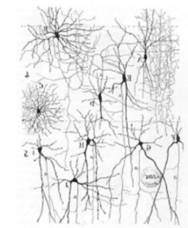
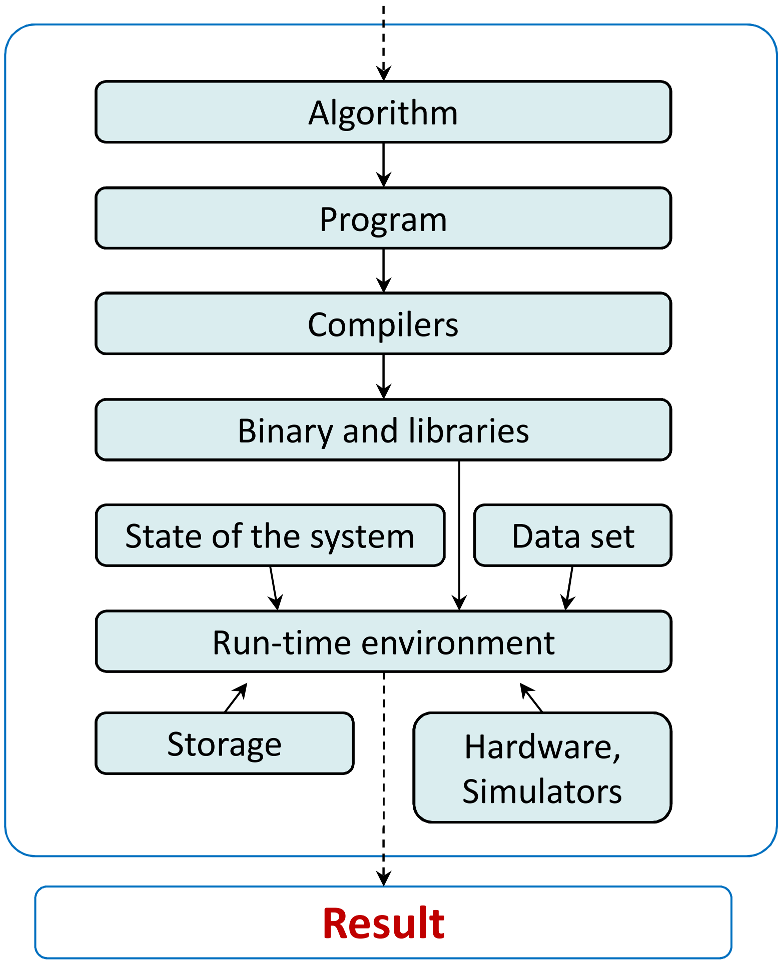




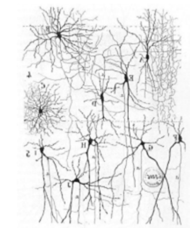
Computer systems' researchers, software developers and hardware designers help end-users

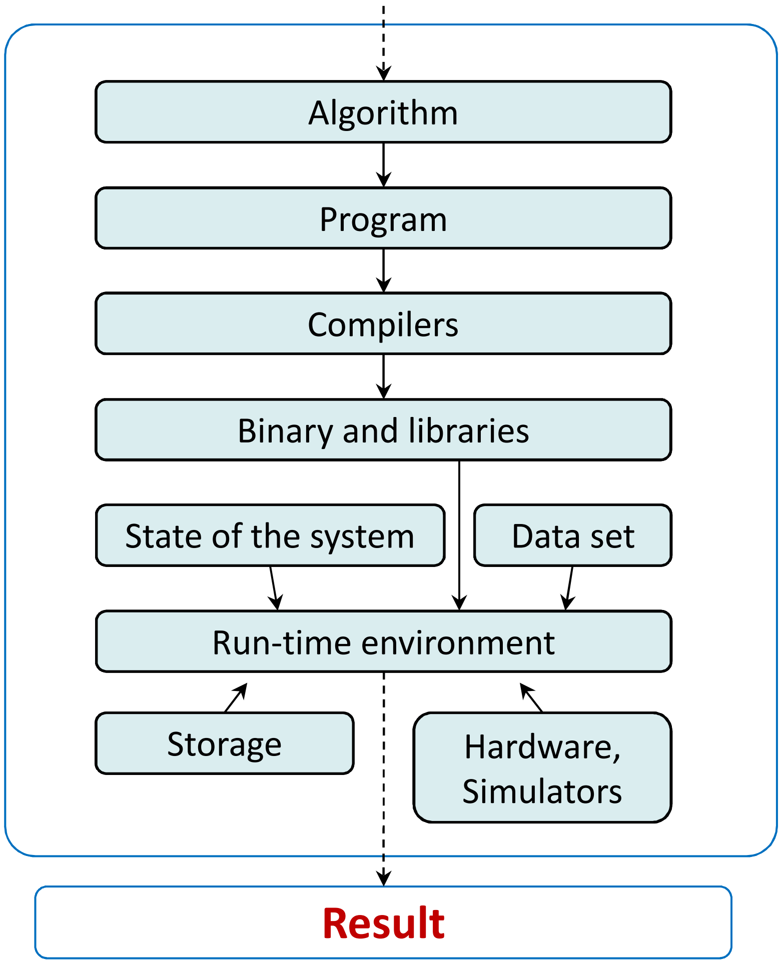
improve all characteristics of their tasks
(execution time, power consumption, numerical instability, size, faults, price …)

guarantee real-time constraints
(bandwidth, QoS, etc)

Two major problems: raising complexity and physical limitations

Finding efficient, reliable and cheap solution for end-user tasks is very non-trivial!





Thousands of ~~benchmarks~~ real applications

MPI, OpenMP, TBB, CUDA, OpenCL, StarPU, OmpSs

C,C++,Fortran,Java,Python,assembler

LLVM,GCC,ICC,PGI (hundreds of optimizations)

BLAS,MAGMA,ViennaCL,cuBLAS,clBLAST,cuDNN, openBLAS, clBLAS

TensorFlow, Caffe, Torch, TensorRT

Infinite number of possible data sets

Linux, Windows, Android, MacOS

heterogeneous, many-core, out-of-order, cache

x86, ARM, PTX, NN, extensions

Numerous architecture and platform simulators

Too many design and optimization choices!

What are you paying for?

Users expect new platforms to be faster, more energy efficient more accurate and more reliable – is it true?

HPC platforms

Mobile devices, sensors, IoT

Supercomputers and data centers cost millions of $ to build, install and use

Weather prediction; physics; medicine; finances

Unchanged algorithms may run only a fraction of peak performance thus wasting expensive resources and energy!

Some years later you may get more efficient algorithms just before new systems arrives!

Smart and powerful mobile devices are everywhere (mobile phones, IoT)

Many attempts to run DNN, HOG, Slam algorithms

Various SW/HW optimizations may result in

7x speedups, 5x energy savings, but poor accuracy

2x speedups without sacrificing accuracy – *enough to enable RT processing*

New systems require further tedious, ad-hoc and error-prone optimization. This slows down innovation and development of new products.

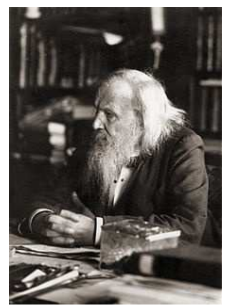
How can we solve these problems?

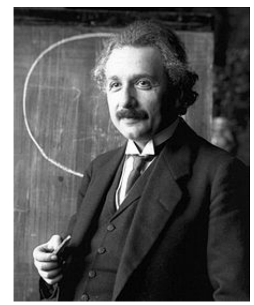
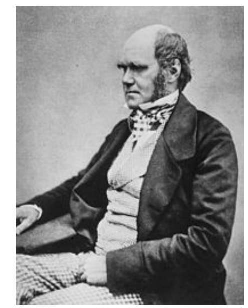
My original background is NOT in computer engineering
but in physics, electronics and machine learning

(first research project in 1994 to develop artificial neural networks chip)

What did I learn from other sciences that deal with complex systems:
physics, mathematics, chemistry, biology, AI …?



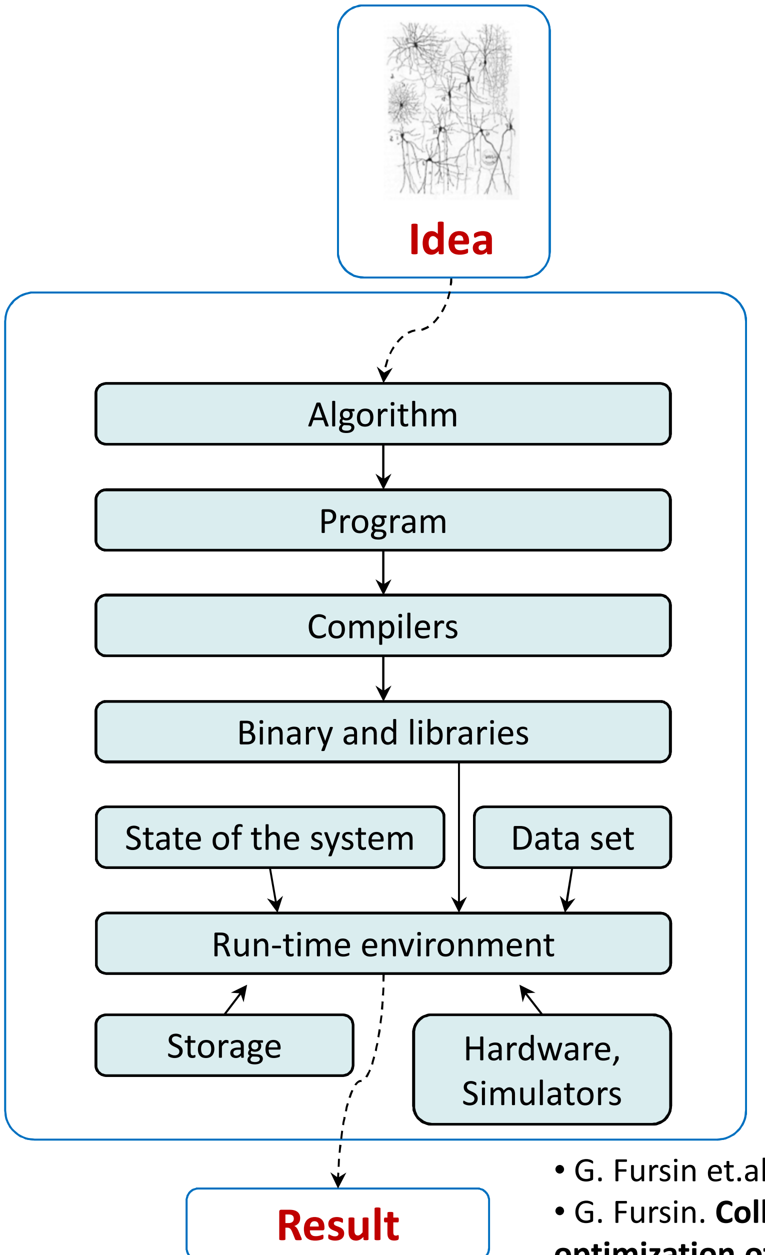



Major breakthroughs came from collaborative and reproducible R&D based on

statistical analysis,
data mining,
machine learning

sharing, validation, systematization
and reuse of artifacts and knowledge!

cTuning.org (2008-cur) – collaborative, machine learning-based optimization



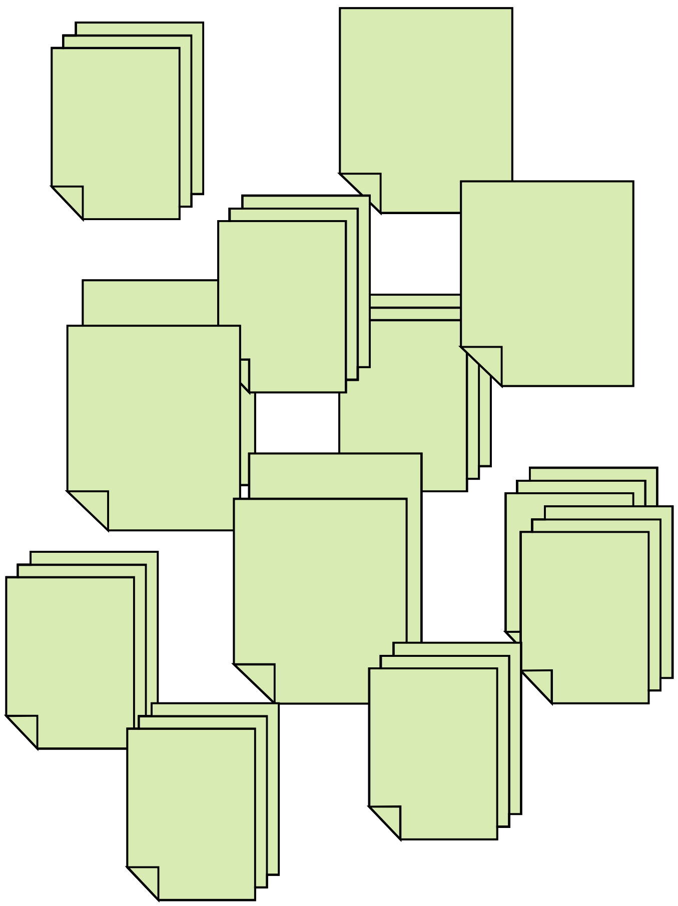
cTuning$_1$ framework and public portal to

1) share realistic benchmarks and data sets
2) share whole experimental setups (benchmarking and autotuning)
3) crowdsource empirical optimization
4) collect results in a centralized repository
5) apply machine learning to predict optimizations
6) involve the community to improve models

- G. Fursin et.al. **MILEPOST GCC: Machine learning based self-tuning compiler.** 2008, 2011
- G. Fursin. **Collective Tuning Initiative: automating and accelerating development and optimization of computing systems,** 2009

cTuning.org/ae (2014-cur.) – artifact evaluation at CGO,PPoPP,PACT,SC

Numerous publications



My personal AE goals

• validate experimental results from published articles and restore trust (see ACM TRUST'14 @ PLDI workshop: cTuning.org/event/acm-trust2014)

• promote artifact sharing (benchmarks, data sets, tools, models)

• enable fair comparison of results and techniques

• develop common methodology for reproducible computer systems' research

• build upon others' research

"Artifact Evaluation for Publications" (Dagstuhl Perspectives Workshop 15452), 2016,
Bruce R. Childers, Grigori Fursin, Shriram Krishnamurthi, Andreas Zeller,
http://drops.dagstuhl.de/opus/volltexte/2016/5762

How Artifact Evaluation (AE) works?

PC members nominate one or two senior PhD students/engineers for AE committee

Pool of reviewers!

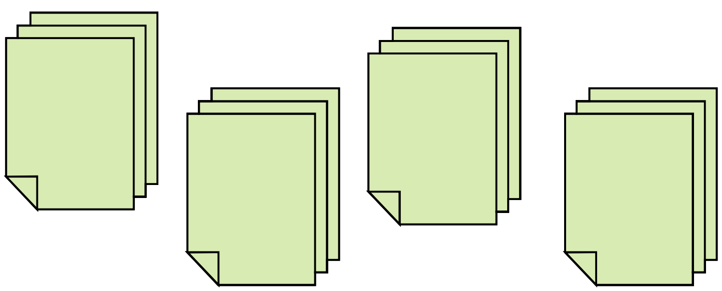
http://ctuning.org/ae/reviewing.html

Formalized reviewing process

Multiple criteria for artifact evaluation

Artifact ranking:

1. **Significantly exceeded expectations**
2. **Exceeded expectations**
3. **Met expectations**
4. **Fell below expectations**
5. **Significantly fell below expectations**



Authors of <u>accepted</u> articles has an option to submit related material for an AE committee to be evaluated

Paper with artifacts which passed evaluation receives AE badge

http://cTuning.org/ae/submission.html

- Abstract
- Packed artifact (or remote access)
- **Artifact Appendix (with a version to keep track of a methodology)**

Artifact evaluation timeline

paper accepted	artifacts submitted	evaluator bidding	artifacts assigned	evaluations available	evaluations finalized	artifact decision
7..12 days	**2..4 days**	**2 days**	**2 weeks**	**3..4 days**	**2..3 days**	**2..3 days**
to prepare artifacts according to guidelines: **cTuning.org/ submission.html**	*for evaluators to bid on artifacts (according to their knowledge and access to required SW/HW)*	*to assign artifacts – ensure at least 3 reviews per artifact, reduce risks, avoid mix ups minimize conflicts of interests*	*to review artifacts according to guidelines:* **cTuning.org/ reviewing.html**	*for authors to respond to reviews and fix problems*	*to finalize reviews*	*to add AE stamp and AE appendix to a camera-ready paper*

time line

Light communication between authors and reviewers is allowed via AE chairs (to preserve anonymity of the reviewers)

Artifact Evaluation: good

- Strong support from academia, industry and ACM
- Active participation in AE discussion sessions
- Lots of feedback
- Many interesting artifacts!

Year	PPoPP	CGO	PACT	Total	Problems	Rejected
2015	10	8		18	**7**	**2** ☹
2016	12	11		23	**4**	**0**
2016			5	5	**2**	**0**
2017	14	13		**27**	**7**	**0**

NOTE: *we consider AE a cooperative process and try to help authors fix artifacts and pass evaluation (particularly if artifacts will be open-sourced)*

We use this practical experience (> 70 papers in the past 3 years!) to continuously improve common experimental methodology for reproducible computer systems' research

ACM taskforce on reproducibility

In 2016 ACM organized a special taskforce (former AE chairs) to develop common methodology for artifact sharing and evaluation across all SIGS!

We produced "***Result and Artifact Review and Badging***" policy:

http://www.acm.org/publications/policies/artifact-review-badging

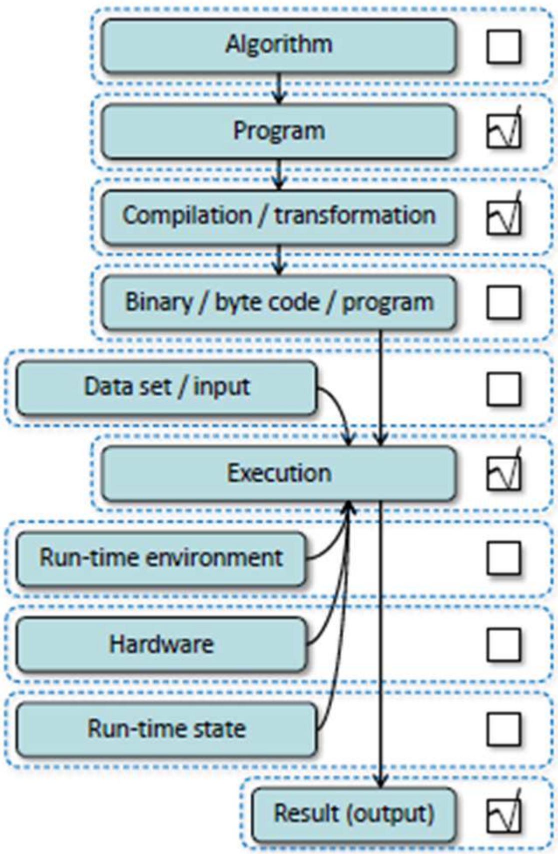
1) Define terminology

Repeatability (Same team, same experimental setup)
Replicability (Different team, same experimental setup)
Reproducibility (Different team, different experimental setup)

2) Prepare new sets of badges (covering various SIGs)

Artifacts Evaluated – Functional
Artifacts Evaluated – Reusable
Artifacts Available
Results Replicated
Results Reproduced

We introduced Artifact Appendices to describe experiments



Two years ago we introduced Artifact Appendix templates to unify Artifact submissions and let authors add up to two pages of such appendices to their camera ready paper:

http://cTuning.org/ae/submission.html
http://cTuning.org/ae/submission_extra.html

The idea is to help readers better understand what was evaluated and let them reproduce published research and build upon it.

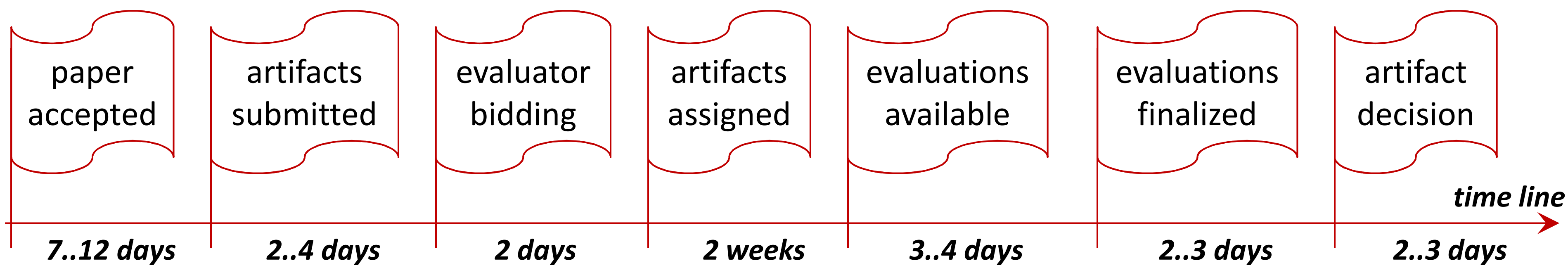
We did not receive complaints about our appendices and many researchers decided to add them to their camera ready papers (see http://cTuning.org/ae/artifacts.html).

Similar AE appendices are now used by other conferences (SC,RTSS):
http://sc17.supercomputing.org/submitters/technical-papers/reproducibility-initiatives-for-technical-papers/artifact-description-paper-title

We are now trying to unify Artifact Appendices across all SIGs

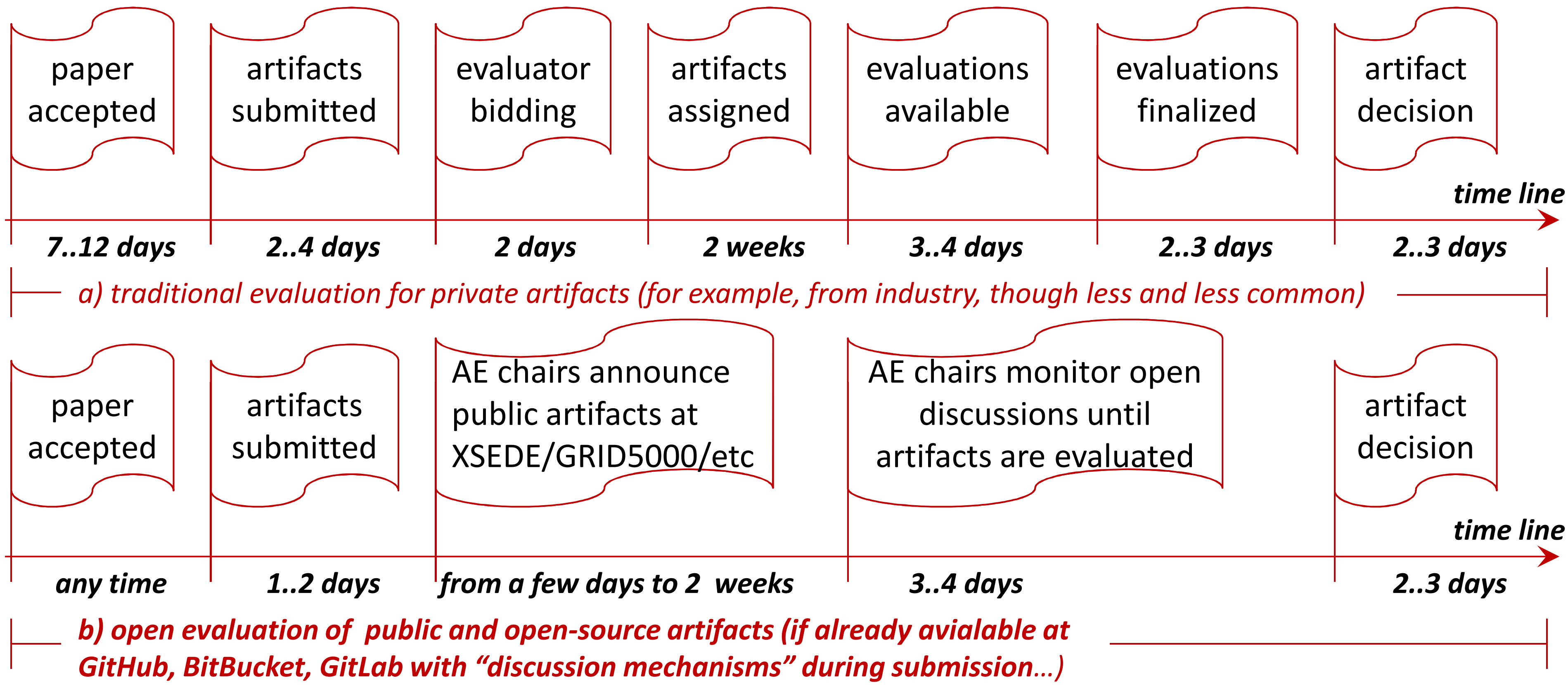
Artifact Evaluation: bad

- too many artifacts to evaluate – need to somehow scale AE while keeping the quality (41 evaluators, ~120 reviews to handle during 2.5 weeks)
- difficult to find evaluators with appropriate skills and access to proprietary SW and rare HW
- very intense schedule and not enough time for rebuttals
- communication between authors and reviewers via AE chairs is a bottleneck



New option of open artifact evaluation!

Introduce two evaluation options: private and public



Trying open artifact and paper evaluation

At CGO/PPoPP'17, we have sent out requests to validate several open-source artifacts to the public mailing lists from the conferences, network of excellence, supercomputer centers, etc.

We found evaluators willing to help and having an access to rare hardware or supercomputers as well as required software and proprietary benchmarks

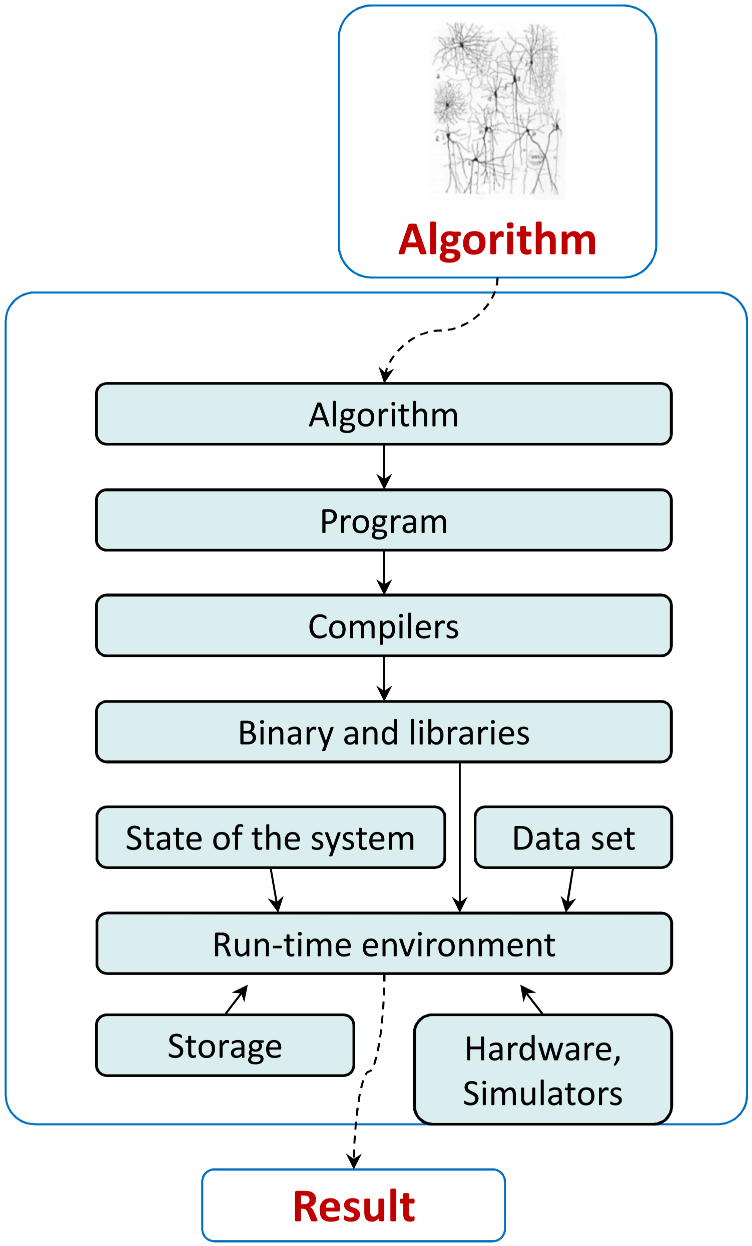
Authors quickly fixed issues and answered research questions while AE chairs steered the discussion!

GRID5000 users participated in open evaluation of a PPoPP'17 artifact:
https://github.com/thu-pacman/self-checkpoint/issues/1

See other public evaluation examples:
cTuning.org/ae/artifacts.html

We validated open reviewing of publications via Reddit at ADAPT'16:
http://adapt-workshop.org

Artifact Evaluation: what can possibly be ugly ;) ?



Ugly: no common experimental methodology and SW/HW chaos

Algorithm

CUDA 7.x LLVM 3.7 function-level pass reordering
LLVM 3.4 ARM v8 MPI OpenCL
OpenMP ICC 11.1 prof gprof
ATLAS CUDA 4.x Intel SandyBridge
LTO GCC 4.2.x per phase TBB
GCC 5.2 LLVM 3.0 reconfiguration
perf
AVX MVS 2013 HMPP memory size
GCC 4.5.x frequency polyhedral XLC
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Testarossa Amplifier
algorithm precision HDD size Open64
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Phoenix

Result

- difficult (sometimes impossible) to reproduce empirical results across ever changing software and hardware stack (highly stochastic behavior)
- everyone uses their own ad-hoc scripts to prepare and run experiments with many hardwired paths
- practically impossible to customize and reuse artifacts (for example, try another compiler, library, data set)
- practically impossible to run on another OS or platform
- no common API and meta information for shared artifacts and results (benchmarks, data sets, tools)

Awarding distinguished artifacts –not enough!

The cTuning foundation and
NVIDIA are pleased to present

Joint CGO/PPoPP Distinguished Artifact Award

for

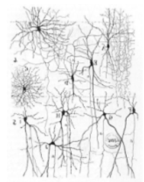
“Demystifying GPU Microarchitecture to Tune SGEMM Performance”

Xiuxia Zhang[1], Guangming Tan[1], Shuangbai Xue[1], Jiajia Li[2], Mingyu Chen[1]

[1] Chinese Academy of Sciences [2] Georgia Institute of Technology

February 2017

Using Virtual Machines and Docker



VM

VM or Docker images
good at hiding complexity

but they do not solve
major problems
in computer systems' research

Result

Docker is useful to archive artifacts while hiding all underlying complexity!

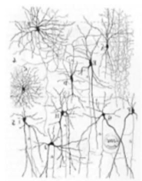
However Docker does not address many other issues vital for open and collaborative computer systems' research, i.e. how to

1) work with a native user SW/HW environment
2) customize and reuse artifacts and workflows
3) capture run-time state
4) deal with hardware dependencies
5) deal with proprietary benchmarks and tools
6) automate validation of experiments

Images are also often too large in size!

Need portable and customizable workflow framework suitable for computer systems research!

Some attempts to clean up this mess in computer systems' R&D



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Phoenix

Result

Third-party resources

cKnowledge.org/reproducibility

Numerous online projects

***But** we want to systematize our local artifacts without being locked up on third-party web services or learn complex GUI*

Better package managers

apt; yum; spack;
pip ; homebrew …

Smart build tools

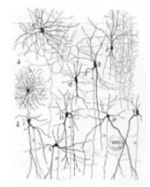
cmake; easybuild …

Multi-versioning

spack; easybuild; virtualenv …

Missing: portable and customizable workflow framework suitable for computer systems' research!

Open-source Collective Knowledge Framework (2015-cur.)



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Phoenix

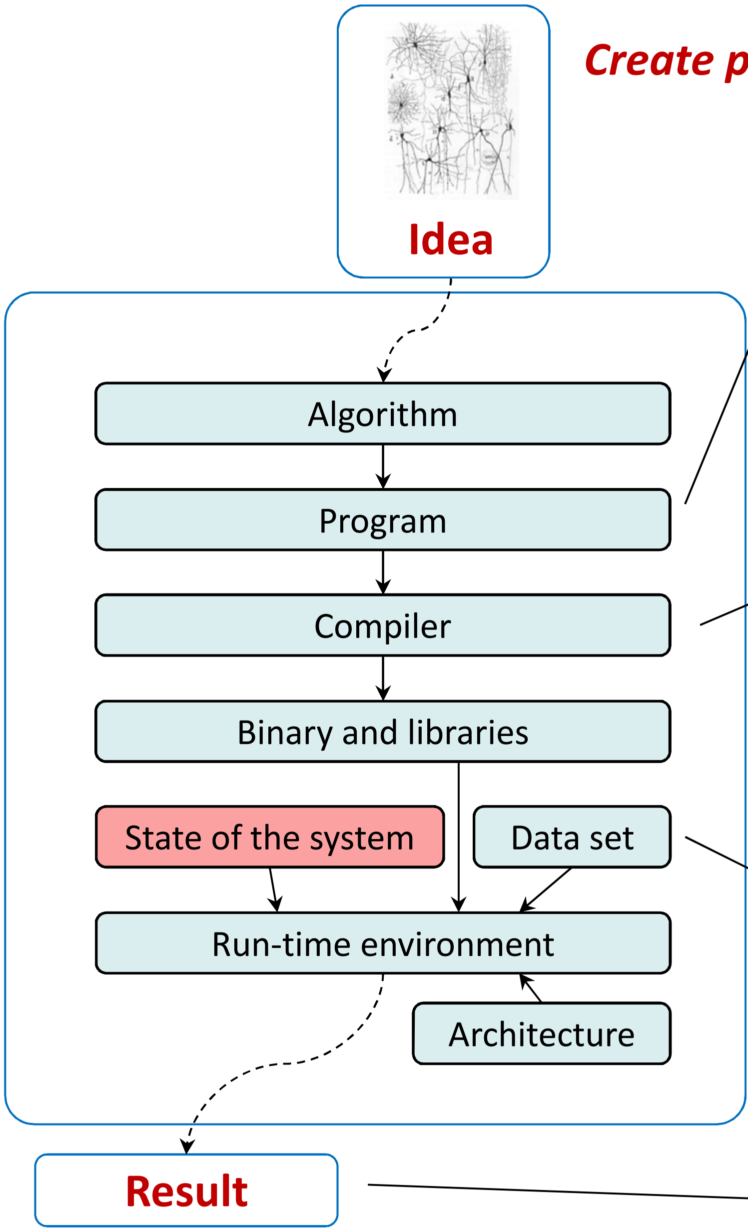
Result

Eventually we didn't have a choices but to use all our experience and develop portable and customizable workflow framework for computer systems' research:

1) organize your artifacts (programs, data sets, tools, scripts) as customizable and reusable components with JSON API and meta data
2) assemble portable and customizable workflows with JSON API from shared artifacts as LEGO ™
3) integrate portable package and environment manager which can detect multiple versions of required software or installed one across Linux, MacOS, Windows and Android
4) integrate web server to show interactive reports (locally!) or exchange data when crowdsourcing experiments

cKnowledge.org ; github.com/ctuning/ck

Noticed during AE: all projects have similar structure



Create project directory

Ad-hoc scripts to compile and run a program…

- image corner detection
- matmul OpenCL
- compression
- neural network CUDA

Have some common meta: *which datasets can use, how to compile, CMD, …*

Ad-hoc scripts to set up environment for a given and possibly proprietary compiler

- GCC V5.2
- LLVM 3.6
- Intel Compilers 2015

Have some common meta: *compilation, linking and optimization flags*

Ad-hoc dirs for data sets with some ad-hoc scripts to find them, extract features, etc

- image-jpeg-0001
- bzip2-0006
- txt-0012
- video-raw-1280x1024

Have some (common) meta: *filename, size, width, height, colors, …*

Ad-hoc dirs and scripts to record and analyze experiments

- cvs speedups
- txt hardware counters
- xls table with graph

Have some common meta: *features, characteristics, optimizations*

Collective Knowledge: organize and share artifacts as reusable components

data UID and alias

Python module
"program"
with functions:
compile and run

- image corner detection
- matmul OpenCL
- compression
- neural network CUDA

meta.json

Python module
"soft"
with function:
setup

- GCC V5.2
- LLVM 3.6
- Intel Compilers 2015

meta.json

Python module
"dataset"
with function:
extract_features

- image-jpeg-0001
- bzip2-0006
- txt-0012
- video-raw-1280x1024

meta.json

Python module
"experiment"
with function:
add, get, analyze

- cvs speedups
- txt hardware counters
- xls table with graph

meta.json

Collective Knowledge: organize and share your artifacts as reusable components

CK: small python module (~200Kb); no extra dependencies; Linux; Win; MacOS

ck <function> <module>:<data UID> @input.json

data UID and alias

JSON input → Python module **"program"** with functions: **compile and run** → *JSON output*

- image corner detection
- matmul OpenCL
- compression
- neural network CUDA

meta.json

JSON input → Python module **"soft"** with function: **setup** → *JSON output*

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JSON input → Python module **"experiment"** with function: **add, get, analyze** → *JSON output*

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meta.json

Collective Knowledge: organize and share your artifacts as reusable components

CK: small python module (~200Kb); no extra dependencies; Linux; Win; MacOS

Connect into workflows as LEGO™

JSON input →

Python module
"program"
with functions:
compile and run

→ Python module
"soft"
with function:
setup

→ Python module
"dataset"
with function:
extract_features

→ Python module
"experiment"
with function:
add, get, analyze

→ *JSON output*

data UID and alias

- image corner detection
- matmul OpenCL
- compression
- neural network CUDA

meta.json

- GCC V5.2
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meta.json

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meta.json

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- txt hardware counters
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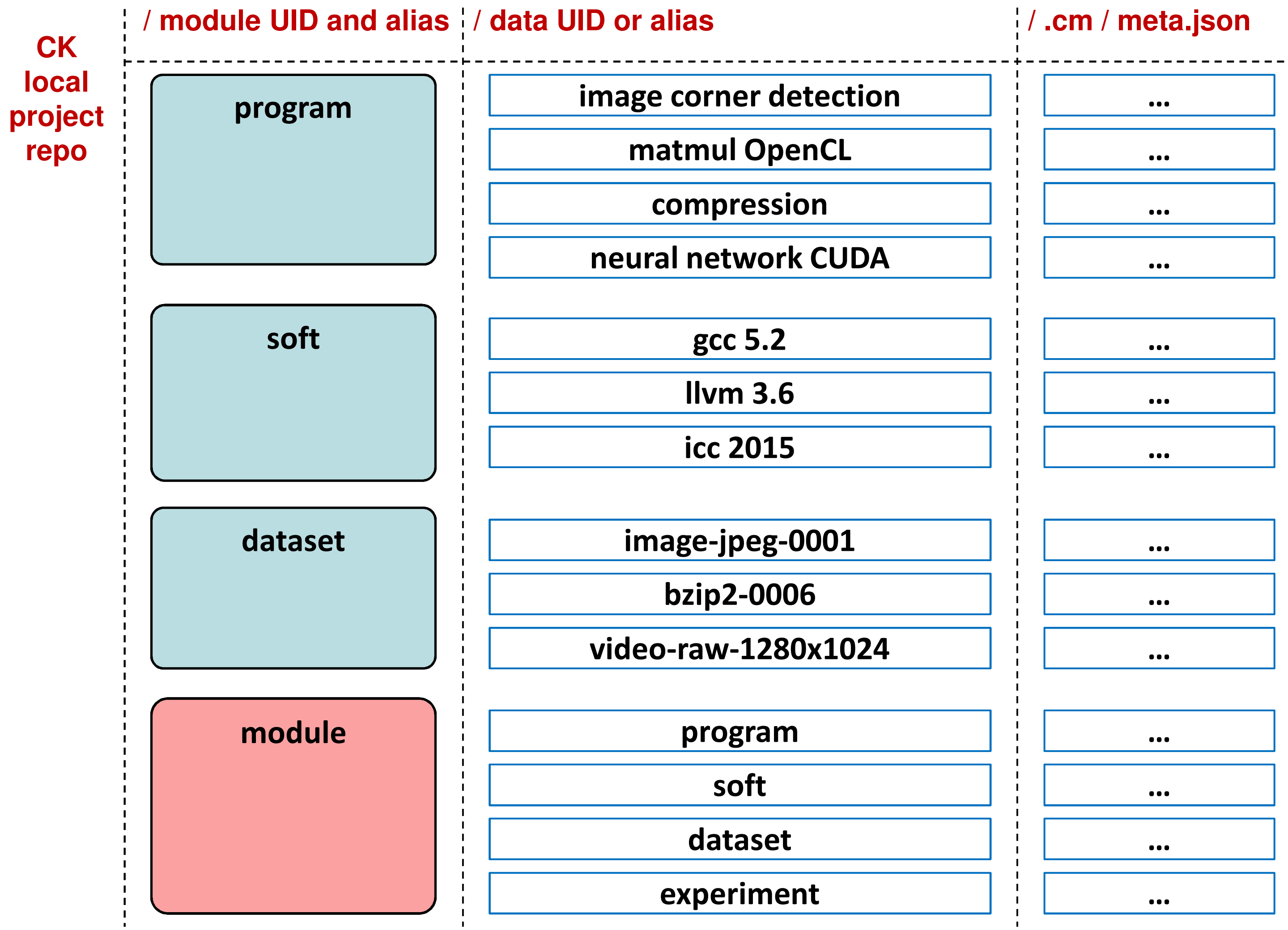
meta.json

Local repository structure (with internal UID and meta)!



Local files – no locks up on third-party web services

No complex GUI

Can be shared via GIT/SVN/etc

Can be easily indexed via ElasticSearch to speed up search

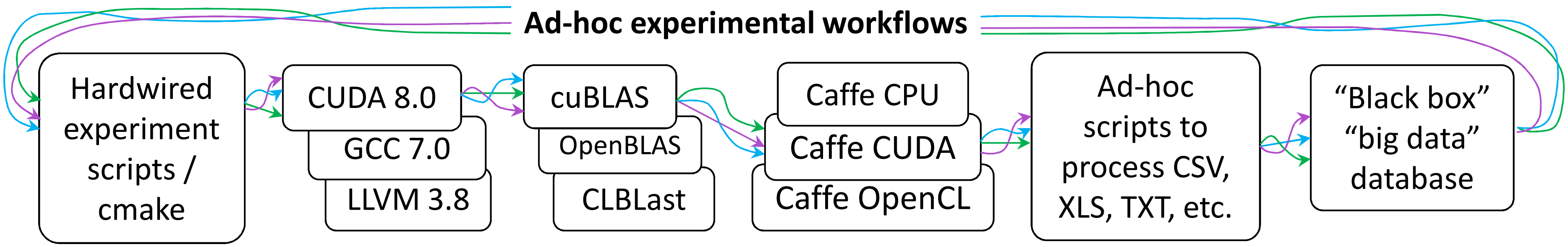
Can be easily connected to Python-based predictive analytics (sklearn-kit)

Both code (with API) and data (with meta) inside repository

Can be referenced and cross-linked via CID (similar to DOI):

module UOA : data UOA

Provide customizable and SW/HW independent access to tools



*Implement SW/HW independent, reusable and shareable CK modules with unified CMD and JSON API for various experimental scenarios (such as **program module**)*

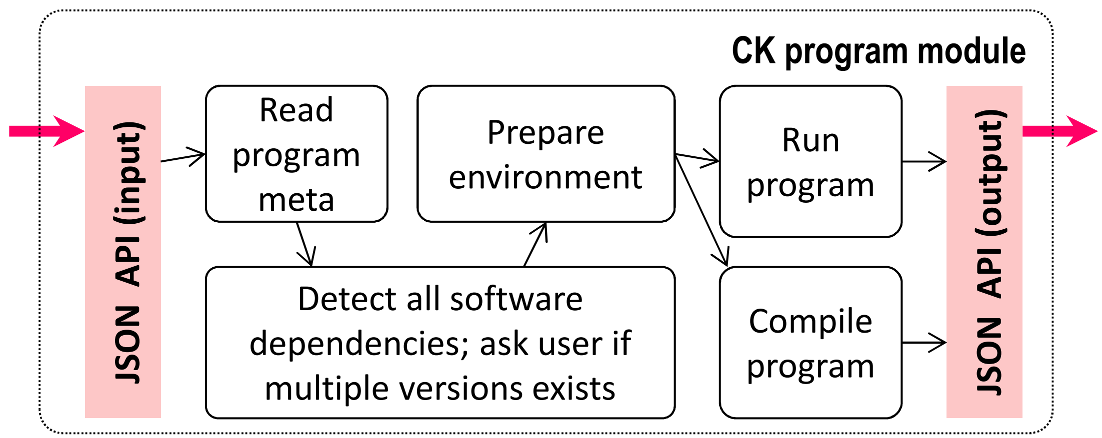
```
$ ck pull repo:ck-autotuning
$ ck compile program:cbench-automotive-susan –speed
$ ck run program:cbench-automotive-susan
$ ck run program:caffe
```

*Use **program entries** to describe a given program in **meta.json** and store sources (if needed)*

CK program entry (*ck list program*)

.cm/meta.json – describes soft dependencies , data sets, and how to compile and run this program

Source files and auxiliary scripts



Portable and customizable package manager in the CK

Works on Linux, Windows, MacOS, Android
Detects multiple versions of various software
Builds missing software
Extended by the community

github.com/ctuning/ck-env

Soft entries in CK describe how to detect if a given software is already installed, how to set up all its environment including all paths (to binaries, libraries, include, aux tools, etc), and how to detect its version.

```
$ ck list soft:compiler*
$ ck search soft --tags=blas
```

```
$ ck detect soft:compiler.gcc
$ ck detect soft --tags=compiler,cuda
$ ck detect soft:compiler.llvm --target_os=android19-arm
$ ck detect soft:lib.cublas
```

Env entries are created in CK local repo for all found software instances together with their meta and an auto-generated environment script **env.sh** (on Linux) or **env.bat** (on Windows).

```
$ ck  show env
$ ck show env –tags=cublas
$ ck rm env:* –tags=cublas
```

Local CK repo

local / env / 03ca0be16962f471 / env.sh
Tags: compiler,cuda,v8.0

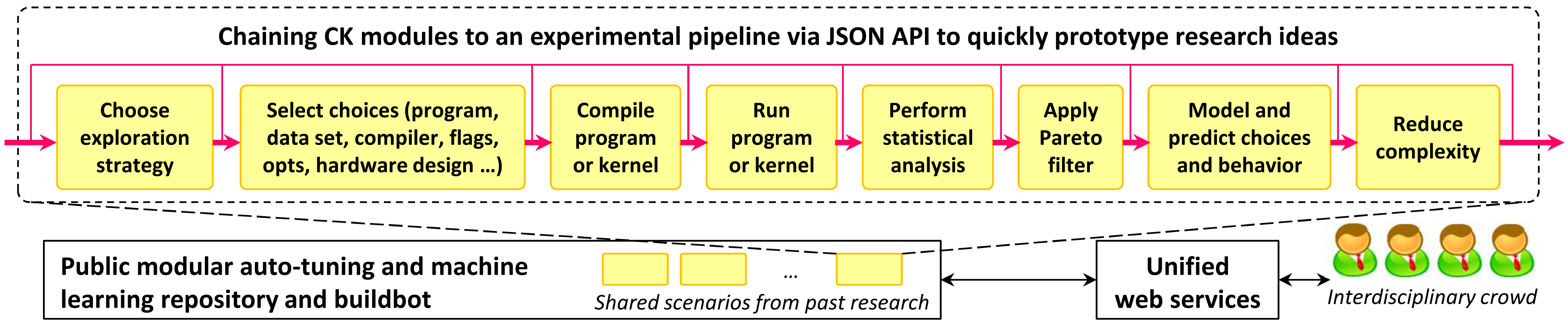
local / env / 0a5ba198d48e3af3 / env.bat
Tags: lib,blas,cublas,v8.0

Package entries describe how to install a given software if it is not installed (using **install.sh** script on Linux host or **install.bat** on Windows host).

```
$ ck list package:*caffemodel*
$ ck search package –tags=caffe
```

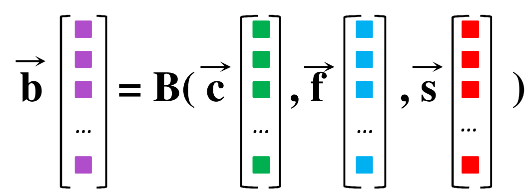
```
$ ck install package:caffemodel-bvlc-googlenet
$ ck install package:imagenet-2012-val
$ ck install package:lib-caffe-bvlc-master-cuda
```

Customizable and reusable workflows with JSON API as LEGO™



Expose and unify information needed for performance analysis and optimization combined with data mining!

Optimizing/modeling behavior **b**
of any object in the CK (program, library function, kernel, …)
as a function of design and optimization choices **c**, features **f**
and run-time state **s**



Flattened JSON vectors

Gradually add JSON specification (depends on research scenario)

Autotuning and machine learning specification:

```
{
  "characteristics":{
    "execution times": ["10.3","10.1","13.3"],
    "code size": "131938", ...},
  "choices":{
    "os":"linux", "os version":"2.6.32-5-amd64",
    "compiler":"gcc", "compiler version":"4.6.3",
    "compiler_flags":"-O3 -fno-if-conversion",
    "platform":{"processor":"intel xeon e5520",
          "l2":"8192“, ...}, ...},
  "features":{
    "semantic features": {"number_of_bb": "24", ...},
    "hardware counters": {"cpi": "1.4" ...}, ... }
  "state":{
    "frequency":"2.27", ...}
}
```

CK flattened JSON key

##characteristics#execution_times@1

```
"flattened_json_key”:{
    "type": "text”|"integer" | “float" | "dict" | "list” | "uid",
    "characteristic": "yes" | "no",
    "feature": "yes" | "no",
    "state": "yes" | "no",
    "has_choice": "yes“ | "no",
    "choices": [ list of strings if categorical choice],
    "explore_start": "start number if numerical range",
    "explore_stop": "stop number if numerical range",
    "explore_step": "step if numerical range",
    "can_be_omitted" : "yes" | "no"
    ...
}
```

The community now use CK to collaboratively tackle old problems

Crowdsource performance analysis and optimization, machine-learning, run-time adaptation across diverse workloads and hardware provided by volunteers

$ sudo pip install ck

$ ck pull repo:ck-crowdtuning

$ ck crowdtune program --gcc

- "**Collective Mind: Towards practical and collaborative autotuning**“, Journal of Scientific Programming 22 (4), 2014
  http://hal.inria.fr/hal-01054763
- “**Collective Mind, Part II: Towards Performance- and Cost-Aware Software Engineering as a Natural Science**”, CPC 2015, London, UK
  http://arxiv.org/abs/1506.06256
- **Android application to crowdsource autotuning across mobile devices:**
  https://play.google.com/store/apps/details?id=openscience.crowdsource.experiments
- “**Collective Knowledge: towards R&D sustainability**”, DATE 2016, Dresden, Germany
  http://bit.ly/ck-date16
- “**Optimizing convolutional neural networks on embedded platforms with OpenCL**”, IWOCL 2016, Amsterdam
  http://dl.acm.org/citation.cfm?id=2909449

Reproducibility of experimental results as a side effect

Reproducibility came as a side effect!

- Can preserve the whole experimental setup with all data and software dependencies
- Can perform statistical analysis for characteristics
- Community can add missing features or improve machine learning models

Execution time:

10 sec.

Reproducibility of experimental results as a side effect

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- Community can add missing features or improve machine learning models

Variation of experimental results:

10 ± 5 secs.

Reproducibility of experimental results as a side effect

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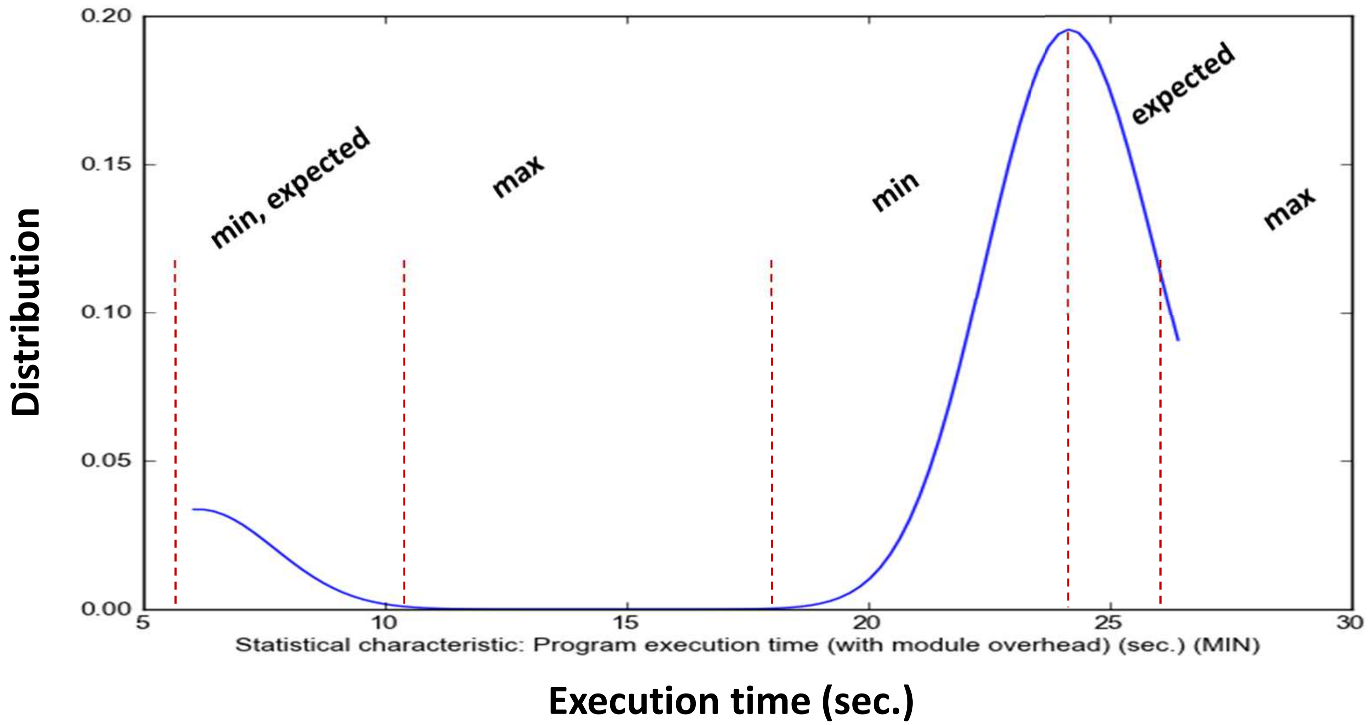
- Community can add missing features or improve machine learning models

Unexpected behavior - expose to the community including experts to explain, find missing feature and add to the system



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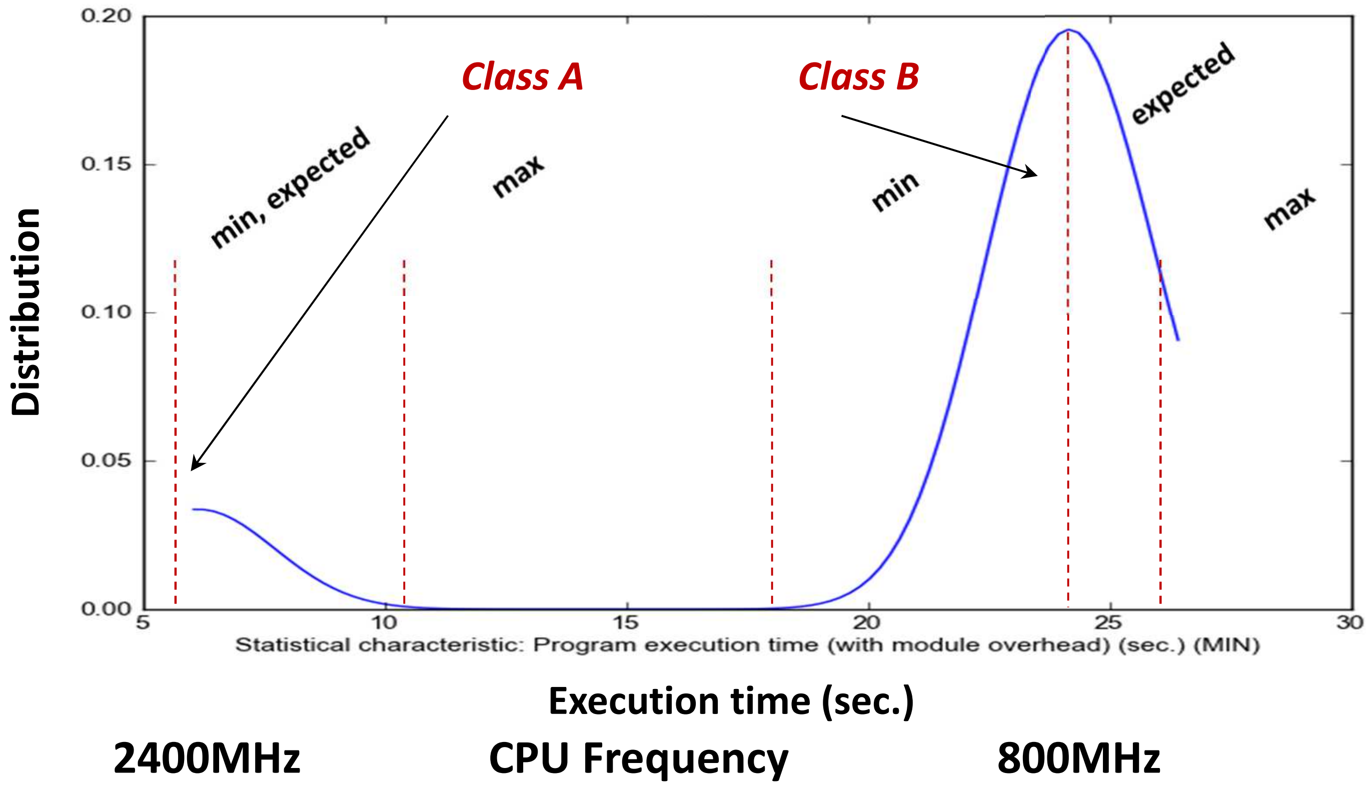


Gradually extend/fix shared workflows by the community during AE

- **Init pipeline**
- Detected system information
- Initialize parameters
- Prepare dataset
- **Clean program**
- **Prepare compiler flags**
- Use compiler profiling
- Use cTuning CC/MILEPOST GCC for fine-grain program analysis and tuning
- Use universal Alchemist plugin (with any OpenME-compatible compiler or tool)
- Use Alchemist plugin (currently for GCC)
- **Compile program**
- Get objdump and md5sum (if supported)
- Use OpenME for fine-grain program analysis and online tuning (build & run)
- Use 'Intel VTune Amplifier' to collect hardware counters
- Use 'perf' to collect hardware counters
- Set frequency (in Unix, if supported)
- Get system state before execution
- **Run program**
- Check output for correctness (use dataset UID to save different outputs)
- Finish OpenME
- Misc info
- **Observed characteristics**
- Observed statistical characteristics
- **Finalize pipeline**

We've shared and continuously extend our experimental workflow for autotuning:

http://github.com/ctuning/ck-autotuning

http://cknowledge.org/repo
http://github.com/ctuning

- Hundreds of benchmarks/kernels/codelets (CPU, OpenMP, OpenCL, CUDA)
- Thousands of data sets
- Wrappers around all main tools and libs
- Optimization description of major compilers

Distinguished CGO'17 artifact in Collective Knowledge format

Highest ranked artifact at CGO'17 turned out to be implemented using Collective Knowledge Framework

"Software Prefetching for Indirect Memory Accesses", Sam Ainsworth and Timothy M. Jones

https://github.com/SamAinsworth/reproduce-cgo2017-paper

It take advantage of a portable package manager
to install required LLVM for either x86 or ARM platforms,
automatically build LLVM plugins,
run empirical experiments on a user machine via CK workflow,
compare speedups with pre-recorded results by authors,
and prepare interactive report

See PDF with Artifact Evaluation Appendix:
http://ctuning.org/ae/resources/paper-with-distinguished-ck-artifact-and-ae-appendix-cgo2017.pdf

See snapshot of an interactive CK dashboard:
https://github.com/SamAinsworth/reproduce-cgo2017-paper/files/618737/ck-aarch64-dashboard.pdf

Collective Knowledge mini-tutorials

Create repository:	**ck add repo:my_new_project**
Add new module:	**ck add my_new_project:module:my_module**
Add new data for this module:	**ck add my_new_project:my_module:my_data @@dict** *{"tags":"cool","data"}*
Add dummy function to module:	**ck add_action my_module –func=my_func**
Test dummy function:	**ck my_func my_module --param1=var1**
List my_module data:	**ck list my_module**
Find data by tags:	**ck search my_module –tags=cool**
Archive repository:	**ck zip repo:my_new_project**
Pull existing repo from GitHub:	**ck pull repo:ck-autotuning**
List modules from this repo:	**ck list ck-autotuning:module:***
Compile program (using GCC):	**ck compile program: cbench-automotive-susan --speed**
Run program:	**ck run program: cbench-automotive-susan**
Start server for crowdsourcing:	**ck start web**
View interactive articles:	**ck browser http://localhost:3344**

http://cKnowledge.org

https://github.com/ctuning/ck/wiki

CK demo: workflow to collaboratively optimizing DNN

- "Deep" (multi-layered) neural networks that take advantage of structure in digital signals (e.g. images).
- State-of-the-art for applications in automotive, robotics, healthcare, entertainment (e.g. image classification).
- Commonly trained on workstations or clusters with GPGPUs.
- Increasingly deployed on mobile and embedded systems.

Difficult and time consuming to build and optimize due to multiple programming models, multiple objectives (performance, energy, accuracy, memory footprint) and continuously evolving hardware particularly with constrained resources (sensors, IoT)

Perfect use case for Collective Knowledge Framework!

Deploying DNNs on resource-constrained platforms

NVIDIA Drive PX2	~ 250 Watts	~ $15,000 *(early development boards)* ~ $1,000 per unit?
?	< 10 Watts	< $100

- Can we deploy a DNN to achieve desired performance (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 (autotune) another DNN (topology) by trading off performance, accuracy and costs?

Customizable CK workflow to collaborative co-design DNN

We collaborate with General Motors and ARM to develop open-source CK-based tools to collaboratively evaluate and optimize various DNN engines and models across diverse platforms and datasets

cKnowledge.org/ai
cKnowledge.org/repo

Download Android app to participate in collaborative evaluation and optimization of DNN using your mobile device and CK web-service:
http://cknowledge.org/android-apps.html

CK portable workflow systems and package manager allows users to run DNN experiments on Windows, Linux, MacOS, Android!

```
$ ck pull repo  --url=http://github.com/dividiti/ck-caffe
$ ck install package:lib-caffe-bvlc-master-cpu-universal
$ ck install package:lib-caffe-bvlc-opencl-viennacl-universal  --target_os=android21-arm64
$ ck run program:caffe-classification
$ firefox http://cKnowledge.org/repo
```

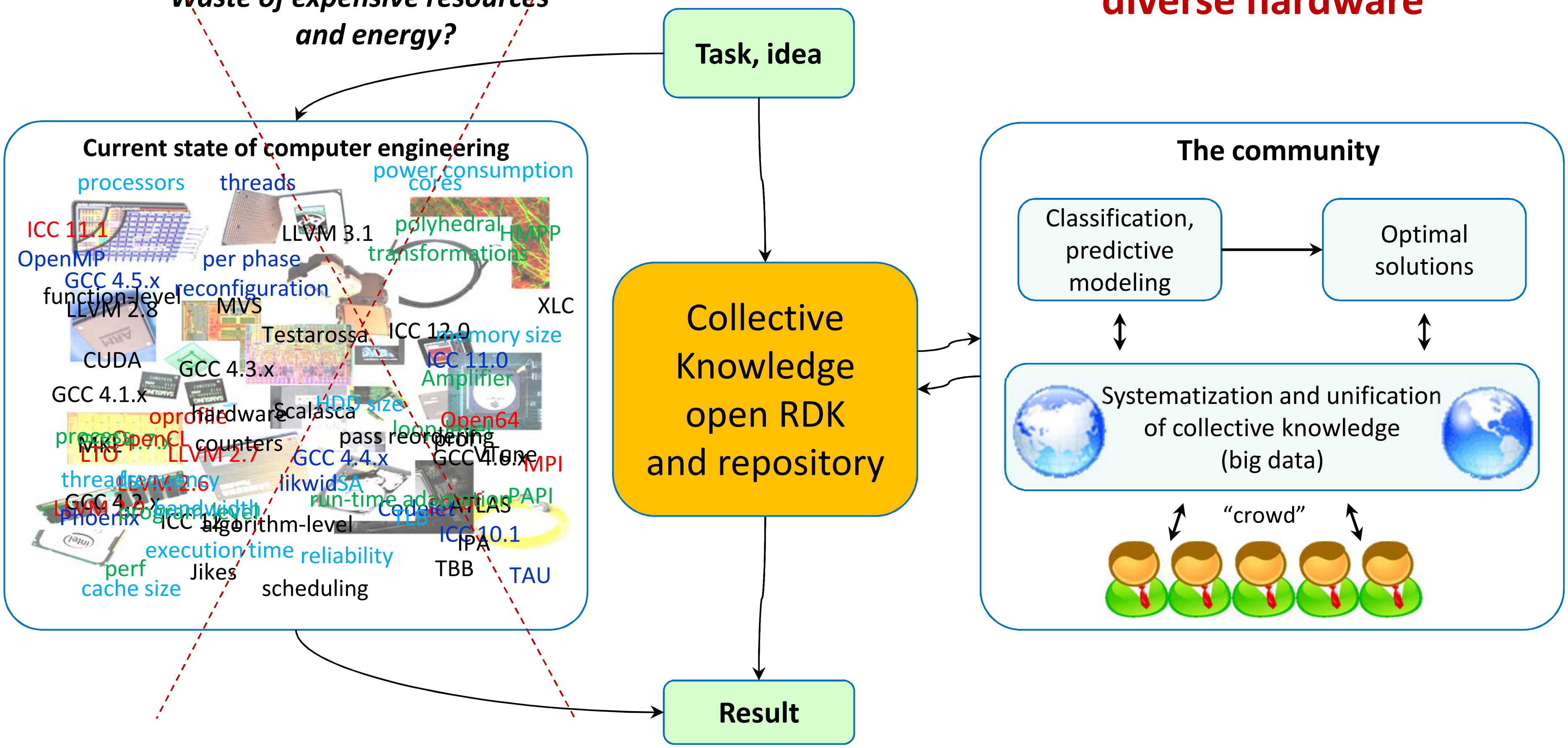
cKnowledge.org: from ad-hoc computer systems' research to data science

- **Collective Knowledge approach helps fight SW/HW chaos**
- **CK is also changing the mentality of computer systems' researchers:**
  - sharing artifacts as customizable and reusable components with JSON API
  - sharing customizable and portable experimental workflows
  - building a repository of representative benchmarks and data sets
  - crowdsourcing experiments and sharing negative/unexpected results
  - collaboratively improving reproducibility of empirical experiments
  - using data mining (statistical analysis and machine learning) to predict efficient software optimizations and hardware designs
  - collaboratively improving prediction models and finding missing features
  - formulating and solving important real-world problems
- **CK brings closer together industry and academia (common research methodology, reproducible experiments, validated techniques)**

cKnowledge.org: enable open & reproducible computer systems' research!

Quick, non-reproducible hack?
Ad-hoc heuristic?
Quick publication?
Waste of expensive resources and energy?

Collaboratively optimize shared programs and data sets across diverse hardware



Extrapolate shared knowledge to build fast, energy efficient, reliable and cheap computer systems to boost innovation in science and technology!

Help us improve artifact evaluation!

We need your feedback - remember that new AE procedures may affect you at the future conferences

- AE steering committee: **http://cTuning.org/ae/committee.html**
- Mailing list: **https://groups.google.com/forum/#!forum/collective-knowledge**

Feel free to reuse and improve our Artifact Evaluation procedures and Artifact Appendices:

http://cTuning.org/ae **https://github.com/ctuning/ck-artifact-evaluation**

Extra resources

- ACM Result and Artifact Review and Badging policy:
  http://www.acm.org/publications/policies/artifact-review-badging
- Community driven artifact evaluation and paper reviewing:
  http://dl.acm.org/citation.cfm?doid=2618137.2618142

Questions, comments, collaborations?

Acknowledgments

ARM

UNIVERSITY OF CAMBRIDGE

GM

acm Association for Computing Machinery

Science & Technology Facilities Council

xored

Inria

The University of Edinburgh

Microsoft Research

Imperial College London

University of Pittsburgh

Many new exciting opportunities for collaboration

Artifact sharing, customizable and portable workflows, experiment crowdsourcing, collaborative deep learning optimization, public repositores of knowledge, adaptive systems

Contact: Grigori.Fursin@cTuning.org

cTuning Foundation

Validated by the community

Powered by Collective Knowledge Framework

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