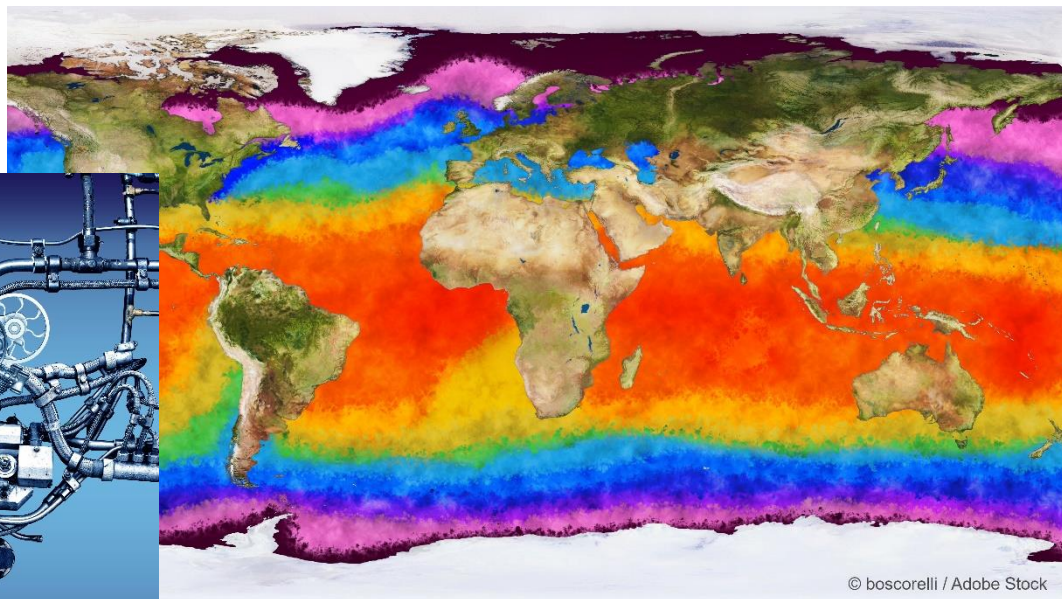
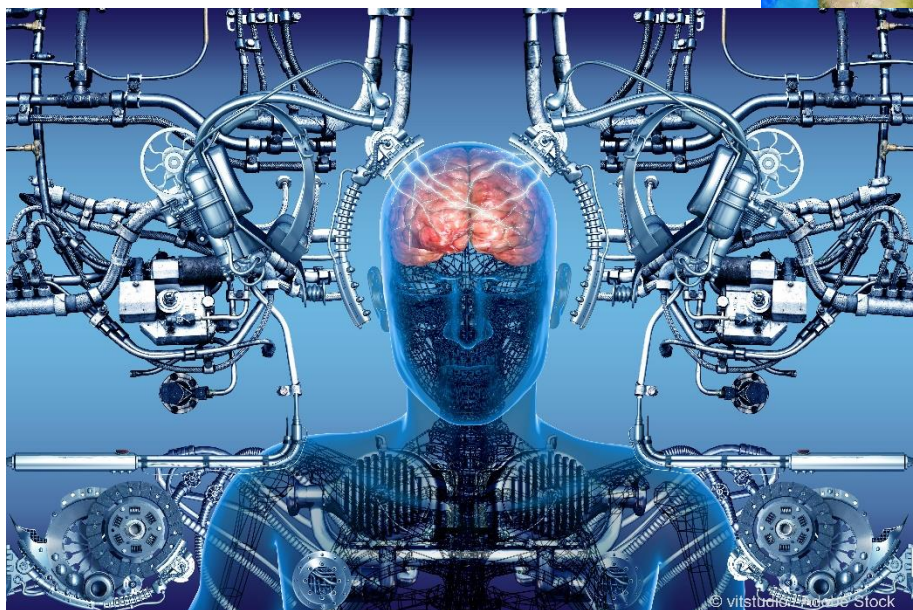


Collective Knowledge framework to automate, crowdsource, reproduce and share HPC experiments



Grigori Fursin (@grigori_fursin)

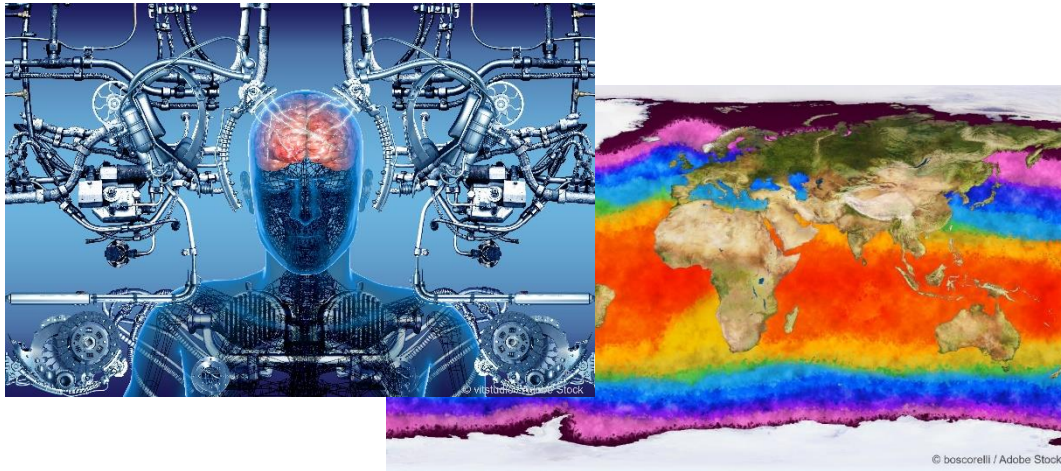
Founder and CEO, non-profit cTuning foundation, France
Co-founder and CTO, dividiti, UK

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

AI, ML, systems and quantum research is booming - 1000+ papers every year ...

Applications

- Meteorology
- Health
- Robotics
- Automotive
- Economics
- Physics
- Astronomy
- Education



Platforms

- HPC
- Desktops
- IoT
- Mobile
- Cloud services

Many great tools, data sets and models to help researchers ...

Applications

- Meteorology
- Health
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- Automotive
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Scientific tools

- MATLAB
- Scilab
- Simulink
- LabVIEW
- Gnuplot
- LaTeX
- Ipython

Build tools

- Make
- Cmake
- SCons
- Bazel
- Gradle
- Ninja

Languages

- C++
- C#
- C
- Go
- PHP
- Fortran
- Java
- Python

Compilers

- LLVM
- GCC
- Intel
- PGI
- TVM
- CUDA

DevOps tools

- Git
- Jenkins
- Docker
- Kubernetes
- Singularity

Package managers

- Anaconda
- Go
- Npm
- Pip
- Sbt
- dpkg
- Spack
- EasyBuild

Libraries

- SciPy
- TFLite
- OpenBLAS
- MAGMA
- cuDNN
- cuFFT
- ArmNN
- CLBlast
- gemmlowp
- Boost
- HDF5
- MPI
- OpenCV
- Protobuf

OS

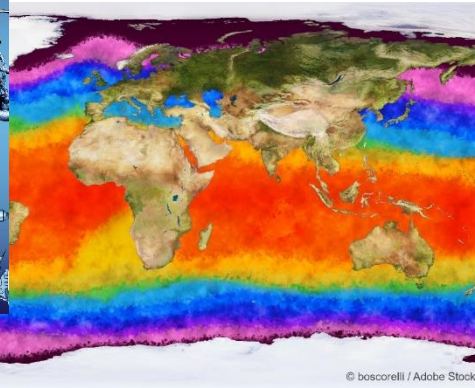
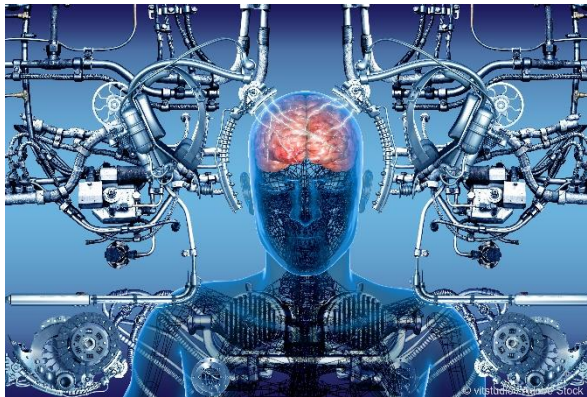
- Linux
- MacOS
- BSD
- Windows
- Android

Shells

- bash
- sh
- csh
- ksh
- Windows shell

Programs

- Image classification
- Object detection
- Natural Language processing
- Text processing
- Video processing
- Personal assistant



AI/ML frameworks

- TensorFlow
- PyTorch
- MXNet
- Caffe
- MCT (CNTK)
- Keras
- Kubeflow
- AutoML
- SageMaker
- Apache Spark

Models

- GoogleNet
- AlexNet
- VGG
- ResNet
- MobileNets
- SSD
- SqueezeNet
- DeepSpeech

Datasets

- ImageNet
- KITTI
- COCO
- MiDataSets
- Human Cell Atlas
- 1000 Genomes
- Earth models
- OpenStreetMap

Workload managers

- MPI
- SLURM
- PBS
- FLUX

Web services

- GitHub
- GitLab
- BitBucket
- Travis
- JupyterHub
- Codelabs
- SageMaker

Databases / experiments

- MySQL
- PostgreSQL
- MongoDB
- CouchDB
- Text files
- JSON files
- XLS files

Knowledge sharing

- ArXiv
- ACM DL
- IEEE DL
- GitHub
- Zenodo
- FigShare
- Web pages

Hardware

- CPU
- GPU
- TPU / NN
- DSP
- FPGA
- Quantum
- Simulators
- Interconnects

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How the community run, share, reproduce and reuse experiments

- Download an archive or some container with artifacts from an accepted paper (manually)
- Go to *scripts* directory (ad-hoc *.sh or python scripts, and occasionally Jupyter notebooks)
What if different shell or even OS?
 - Download source code (typically with recursion from GitHub, GitLab, BitBucket)
What if some sources are already available?
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What if URL changed or file is not available?
What if I want to try different datasets or my own ones?
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What if I want to try different models or my own ones? Will they be compatible?
 - Install numerous software dependencies (often manually or semi-manually)
What if some are already installed? Can I reuse them? What if they are newer?
What if they are not available for my system?
 - Compile program and some dependencies (most of the time “automated”)
Of course, it will never fail ;) !!!
 - Run experiments (simulations) and record all results (outputs, performance ...) in raw, text and CSV files (usually semi-automated)
What can possibly go wrong (of course APIs and command lines never change) ;) ?
 - Process results, compare with the paper, and report discrepancies (often manually)
That's the simplest part - just check 5 tables, 10 graphs, and just spot the difference!!!

Let's hide the mess ...

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 - Do ... (What if different shell or even OS? GitLab, BitBucket)
 - Do ... (already available? included)
 - Do ... (not available? my own ones? included)
 - Do ... (compatible? y)
 - Ins ... (y are newer? for my system?)
- Compile programs (some "automated")
 - Run experiments (sim ...) and record all results (outputs, performance ...) in raw, text and CSV files (usually semi-automated)
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How can we automate all those steps and enable DevOps?

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PI-API: validate results from *a program* using *pre-recorded ones*, auto-generate paper

Collective Knowledge basics: github.com/ctuning/ck/wiki and [cKnowledge.org](https://cknowledge.org)

\$ sudo pip install **ck**

Now can implement, share and reuse APIs as Python [modules](#) via CK repositories

Collective Knowledge basics: github.com/ctuning/ck/wiki and cKnowledge.org

```
$ sudo pip install ck
```

Now can implement, share and reuse APIs as Python [modules](#) via CK repositories

```
$ ck add repo:my-paper --quiet
```

Local directory: \$HOME/CK/[my-paper](#)/.ckr.json (repo description and dependencies)

```
$ ck ls repo or ck search repo
```

[my-paper](#) [local](#) [default](#)

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[my-paper](#) [local](#) [default](#)

```
$ ck add my-paper:module:hello
```

```
$ ck add_action module:hello --func=say
```

Local directory: \$HOME / CK / [my-paper](#) / [module](#) / [hello](#) / module.py

\$HOME / CK / [my-paper](#) / [module](#) / [hello](#) / .cm / [meta.json](#)

```
def say(i):  
    print (json.dumps(i))  
    actions=cfg['actions']  
    return {'return':0, 'error':")
```

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\$HOME / CK / my-paper / module / hello / .cm / meta.json

```
$ ck say hello --fosdem --is=cool @input.json
```

```
{ "action": "say", "module_uoa": "hello", "fosdem": "yes", "is": "cool" ... }
```

```
$ python (or Jupyter notebooks)
```

```
import ck.kernel as ck
```

```
r=ck.access({"action": "say", "module_uoa": "hello", "fosdem": "yes", "is": "cool"})
```

```
print (r)
```

```
{'return':0}
```

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def say(i):  
    print (json.dumps(i))  
    actions=cfg['actions']  
    return {'return':0, 'error': ''}
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```

```
import ck.kernel as ck
```

```
r=ck.access({"action": "say", "module_uoa": "hello", "fosdem": "yes", "is": "cool"})
```

```
print (r)
```

```
{'return':0}
```

```
$ ck add my-paper:hello:world --tags=fosdem,20190203
```

Local directory: \$HOME / CK / my-paper / hello / world / .cm / meta.json

\$HOME / CK / my-paper / hello / world / <- holder for files and dirs

```
$ ck search hello --tags=fosdem --all
```

```
def say(i):  
    print (json.dumps(i))  
    actions=cfg['actions']  
    return {'return':0, 'error': ''}
```

```
{ "tags":["fosdem","20190203"] }
```

Collective Knowledge basics: github.com/ctuning/ck/wiki and [cKnowledge.org](https://cknowledge.org)

```
$ sudo pip install ck
```

*Now can implement, share and reuse APIs as Python **modules** via CK repositories*

```
$ ck add repo:my-paper --quiet
```

Local directory: \$HOME/CK/my-paper/.ckr.json (repo description and dependencies)

```
$ ck ls repo or ck search repo
```

my-paper local default

```
$ ck add my-paper:module:hello
```

```
$ ck add_action module:hello --func=say
```

Local directory: \$HOME / CK / my-paper / module / hello / module.py

\$HOME / CK / my-paper / module / hello / .cm / meta.json

```
$ ck say hello --fosdem --is=cool @input.json
```

```
{ "action": "say", "module_uoa": "hello", "fosdem": "yes", "is": "cool" ... }
```

```
$ python (or Jupyter notebooks)
```

```
import ck.kernel as ck
```

```
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```

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```

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```

Local directory: \$HOME / CK / my-paper / hello / world / .cm / meta.json

\$HOME / CK / my-paper / hello / world / <- holder for files and dirs

```
$ ck search hello --tags=fosdem --all
```

```
$ ck load hello:world --min
```

```
{ "tags": ["fosdem", "20190203"] }
```

```
def say(i):  
    print (json.dumps(i))  
    actions=cfg['actions']  
    return {'return':0, 'error': ''}
```

```
{ "tags": ["fosdem", "20190203"] }
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\$HOME / CK / my-paper / module / hello / .cm / meta.json

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$ ck say hello --fosdem --is=cool @input.json
```

```
{ "action": "say", "module_uoa": "hello", "fosdem": "yes", "is": "cool" ... }
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```

Local directory: \$HOME / CK / my-paper / hello / world / .cm / meta.json

\$HOME / CK / my-paper / hello / world / <- holder for files and dirs

```
$ ck search hello --tags=fosdem --all
```

```
$ ck load hello:world --min
```

```
{ "tags": [ "fosdem", "20190203" ] }
```

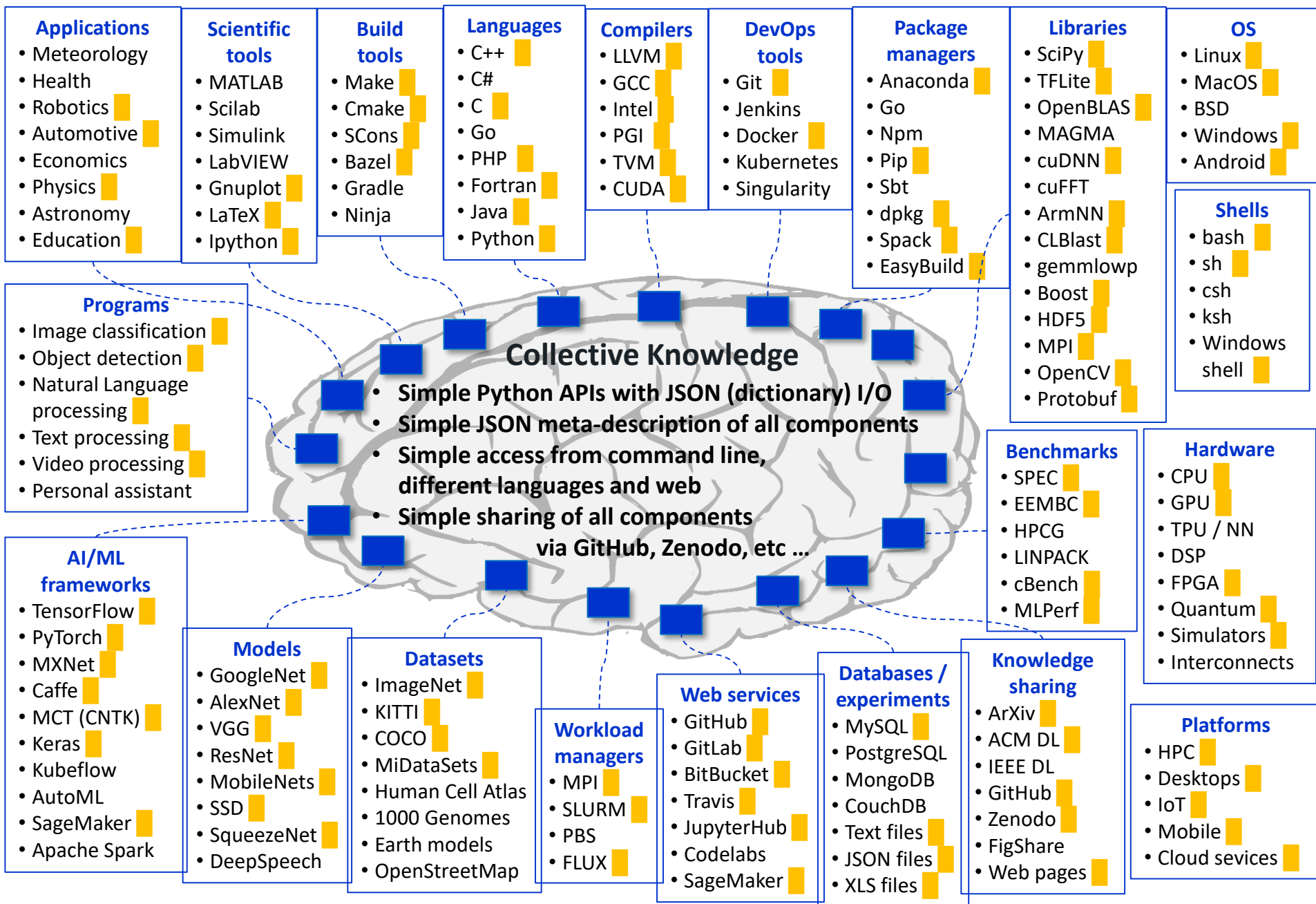
```
$ ck say hello:world -f
```

```
{ "action": "say", "module_uoa": "hello", "data_uoa": "world", "f": "yes" ... }
```

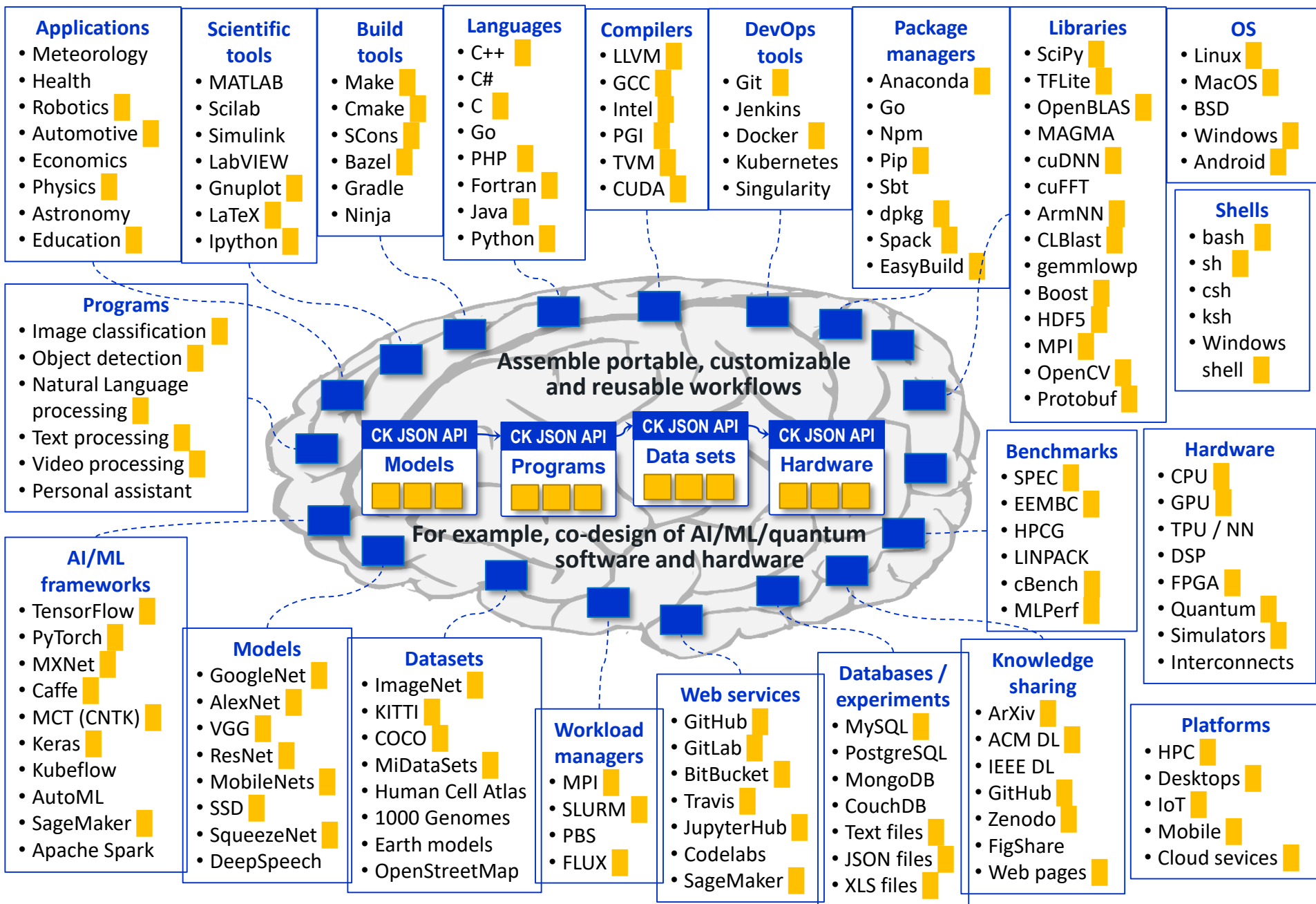
```
def say(i):  
    print (json.dumps(i))  
    actions=cfg['actions']  
    return { 'return': 0, 'error': '' }
```

```
{ "tags": [ "fosdem", "20190203" ] }
```

Collective knowledge: collaboratively abstract, describe and reuse everything!



Implement workflows (pipelines) adaptable to any SW/HW! Focus on innovation!



Anyone can share reusable components (code and data) with common APIs and meta descriptions

Started converting all my own past R&D on autotuning and machine learning to CK

cKnowledge.org/shared-repos.html

cKnowledge.org/shared-modules.html

Artifact

automated and reusable

Collective Knowledge

COMPATIBLE

Workflow

CK

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cKnowledge.org/shared-repos.html

cKnowledge.org/shared-modules.html

Artifact automated and reusable

Collective Knowledge COMPATIBLE

Workflow CK

1) Describing different operating systems (github.com/ctuning/ck-env)

```
$ ck pull repo:ck-env
```

```
$ ck ls os
```

```
$ ck load os:linux-64 --min
```

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```
$ ck pull repo:ck-env
```

```
$ ck ls os
```

```
$ ck load os:linux-64 --min
```

2) Detecting and unifying information about platforms

```
$ ck detect platform --help
```

```
$ ck detect platform --out=json
```

```
$ ck load os:linux-64 --min
```

Anyone can share reusable components (code and data) with common APIs and meta descriptions

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cKnowledge.org/shared-repos.html

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```
$ ck detect platform --help
```

```
$ ck detect platform --out=json
```

```
$ ck load os:linux-64 --min
```

3) Detecting installed “software” (**both** code and data):

```
$ ck search soft --tags=dataset
```

cKnowledge.org/shared-soft-detection-plugins.html

```
$ ck detect soft:compiler.llvm
```

```
$ ck show env --tags=llvm
```

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cKnowledge.org/shared-repos.html

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```
$ ck load os:linux-64 --min
```

3) Detecting installed “software” (**both** code and data):

```
$ ck search soft --tags=dataset
```

cKnowledge.org/shared-soft-detection-plugins.html

```
$ ck detect soft:compiler.llvm
```

```
$ ck show env --tags=llvm
```

4) Installing missing packages (**both** code and data): front-end to EasyBuild, Spack, scons, cmake

```
$ ck search package --tags=model
```

cKnowledge.org/shared-packages.html

```
$ ck install compiler:compiler-llvm-7.0.0-universal
```

```
$ ck show env --tags=llvm
```

```
$ ck virtual env --tags=llvm,v7.0.0
```


Enabling customizable and portable workflows by connecting CK components

Common JSON API

JSON
meta

Algorithm / source code

AI framework

Available libraries / skeletons

Compilers

Binary or byte code

Inputs

Various models

Run-time environment

Run-time state
of the system

Hardware,
simulators

Universal program workflow to compile, run and profile diverse benchmarks with different data sets, validate results, record experiments, share and reproduce them, and report discrepancies

<http://cKnowledge.org/shared-programs.html>

```
$ ck pull repo:ck-crowdtuning
```

```
$ ck ls program
```

```
$ ck ls dataset
```

```
$ ck load program:cbench-automotive-susan --
```

min

```
$ ck compile program:cbench-automotive-  
susan -fast
```

```
$ ck run program:cbench-automotive-susan
```

```
$ ck autotune program:cbench-automotive-
```

susan

```
$ ck crowdtune program:cbench-automotive-
```

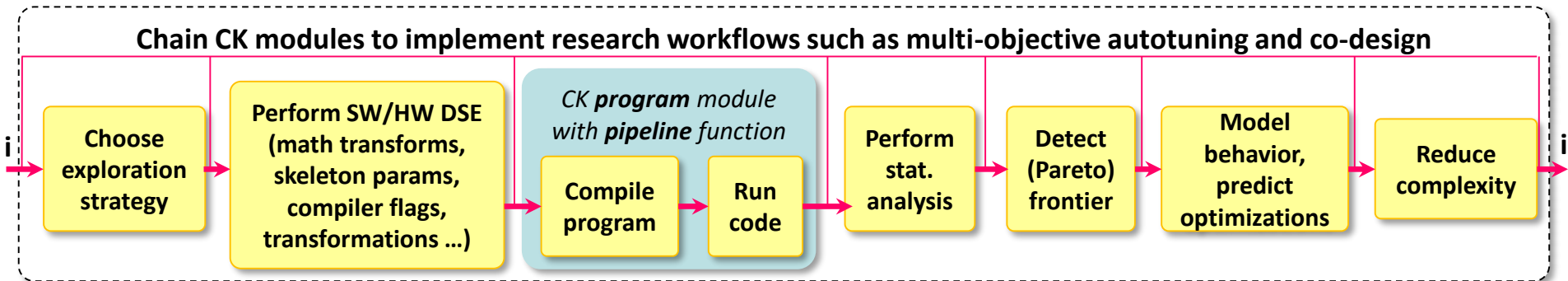
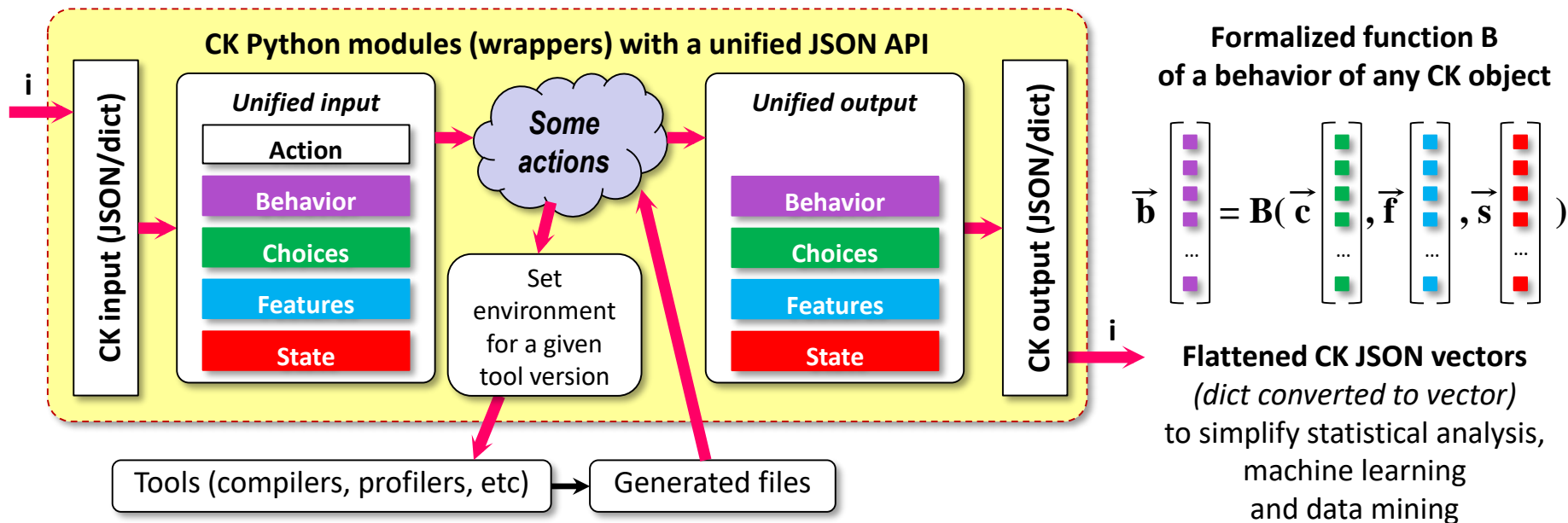
susan

```
$ ck replay experiment
```

Having APIs and JSON meta enables DevOps and easy integration with Jenkins, Travis, etc.
CK complements containers and can be easily used in Jupyter notebooks!

Implementing autotuning pipeline of the whole AI/ML/SW/HW stack!

Collaboratively expose choices, features, system state and behavior characteristics



We can even automatically generate reproducible and interactive articles (collaboration with Raspberry Pi foundation): cKnowledge.org/rpi-crowd-tuning

Real-world use cases with our partners: cKnowledge.org/partners

Repositories of customizable, portable and reusable research components with CK API

cKnowledge.org/shared-repos.html

CK JSON API

AI frameworks

TensorFlow
Caffe
Caffe2
CNTK
Torch
MXNet
...

CK JSON API

Models

AlexNet
GoogleNet
VGG
ResNet
SqueezeDet
SSD
MobileNets
...

CK JSON API

Libraries

cuDNN
ArmCL
OpenBLAS
ViennaCL
CLBlast
cuBLAS
TVM
...

CK JSON API

Data sets

KITTI
COCO
VOC
ImageNet
Real life objects from the community
...

CK JSON API

OS

Linux
MacOS
Windows
Android
...

CK JSON API

Hardware

CPU
GPU
DSP
NN accelerators
FPGA
Simulators
...

Customizable CK workflows
for real-world user tasks

Assemble scenarios such as image classification as LEGO™

CK JSON API

Models

□ □ □

CK JSON API

Software

□ □ □

CK JSON API

Data sets

□ □ □

CK JSON API

Hardware

□ □ □

Share complete workflows along with published papers
to automate artifact evaluation
and help the community build upon prior work

Crowdsource experiments with the help of volunteers
across diverse models, data sets and platforms



Present best results, workflows and components
on a live scoreboard for fair comparison and reuse

cKnowledge.org/repo

Help students learn multidisciplinary techniques,
quickly prototype new ones,
validate them in practice with companies,
and even contribute back new research components

Help companies select the most appropriate workflows,
save R&D costs, accelerate adoption of new techniques!

Open science: organizing reproducible tournaments and sharing research components

2018: many cross-disciplinary R&D groups (ML/AI/systems)

AI hardware

- All major vendors (Google, NVIDIA, ARM, Intel, IBM, Qualcomm, Apple, AMD ...)

AI models

Many groups in academia & industry (Google, OpenAI, Microsoft, Facebook ...)

AI software

- AI frameworks (TensorFlow, MXNet, PyTorch, CNTK, Theano)
- AI libraries (cuDNN, libDNN, ArmCL, OpenBLAS)

AI integration/services

- Cloud services (AWS, Google, Azure ...)

cKnowledge.org/request

Finding the most efficient AI/SW/HW stacks across diverse models, data sets and platforms via open competitions, share them as reusable CK components and visualize on a public scoreboard

Organizers (A-Z)

Luis Ceze, University of Washington
Natalie Enright Jerger, University of Toronto
Babak Falsafi, EPFL
Grigori Fursin, dividiti/cTuning foundation
Anton Lokhmotov, dividiti
Thierry Moreau, University of Washington
Adrian Sampson, Cornell University
Phillip Stanley Marbell, University of Cambridge

Real use-cases

Healthcare
Agriculture
Finances
Automotive
Aerospace
Meteorology
Retail
Robotics
...

Collective Knowledge Platform

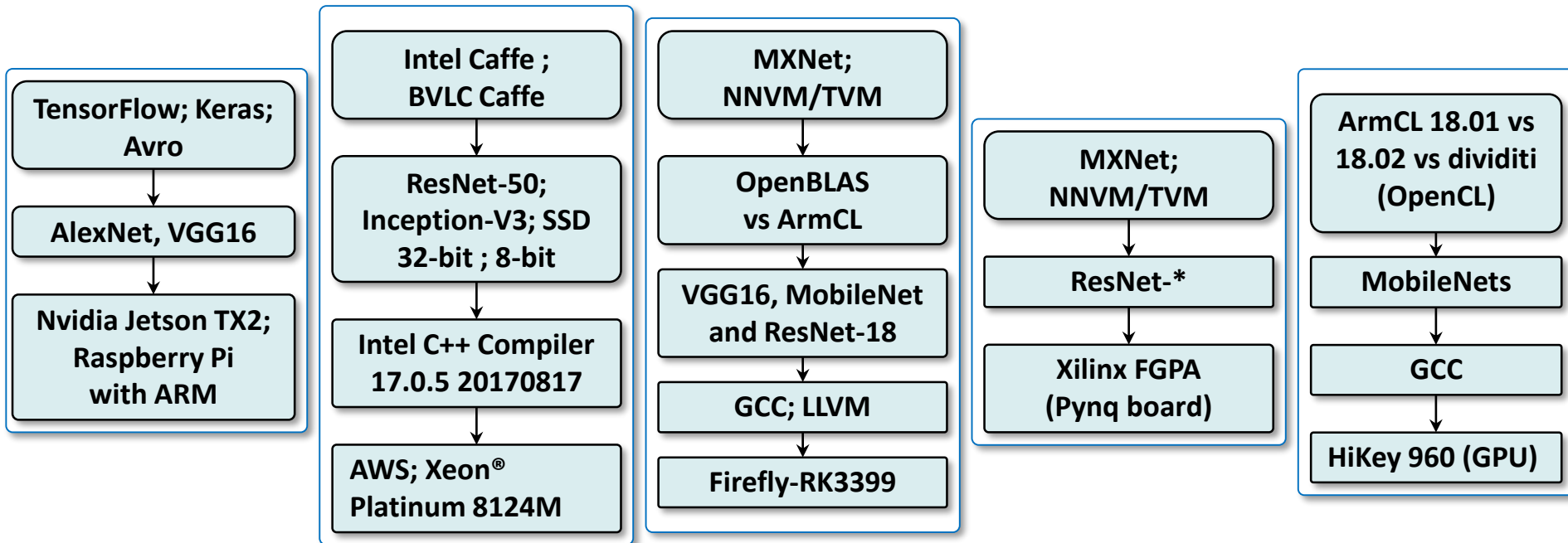


Interdisciplinary community

* Workshop organizers

We organized the 1st reproducible tournament at ACM ASPLOS'18

8 intentions to submit and 5 submitted image classification workflows with unified Artifact Appendices



Public validation at github.com/ctuning/ck-request-asplos18-results via GitHub issues.

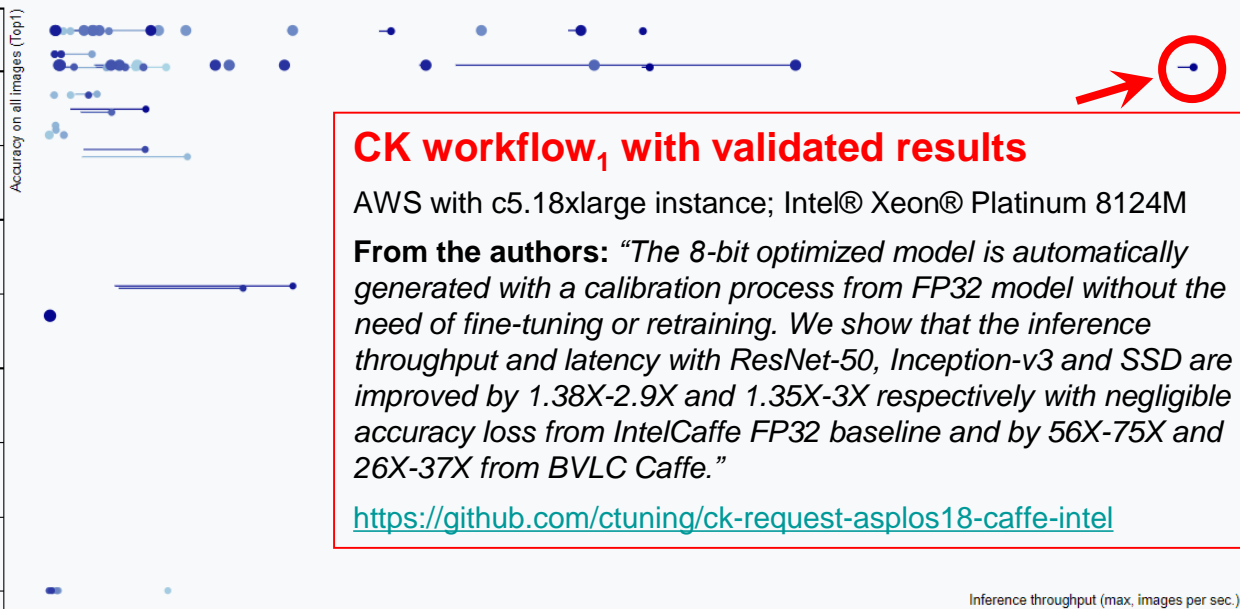
All validated papers are published in the ACM DL
with **portable, customizable and reusable CK components and workflows**:
dl.acm.org/citation.cfm?doid=3229762

See ACM ReQuEST report: portalparts.acm.org/3230000/3229762/fm/frontmatter.pdf

All results and research components are available via a live CK scoreboard

Multi-objective results for all AI/SW/HW stacks are presented on a live scoreboard and become available for public comparison and further customization, optimization and reuse!

ReQuEST @ ASPLOS'18 tournament (Pareto-efficient image classification)



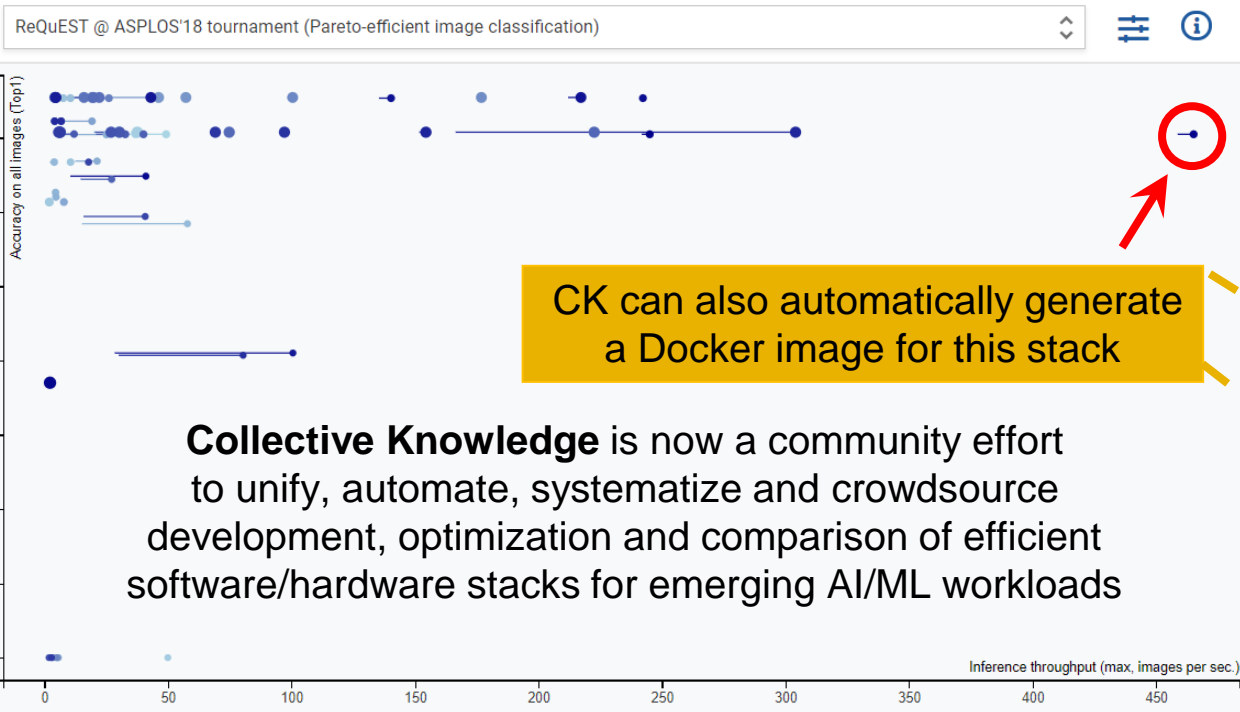
Plot dimension X

Inference throughput (max, images per sec.)
Experiment number
Prediction time per 1 image (min, sec.)
Inference latency for 1 image (min, sec.)
Inference throughput (max, images per sec.)
Accuracy on all images (Top1)
Accuracy on all images (Top5)
Model size (B)
Platform peak power (W)
Platform price (\$)
Usage cost (\$)
Platform species
Model species
Model precision
Dataset species
Device frequency (MHz)
CPU frequency (MHz)
GPU frequency (MHz)
Batch size

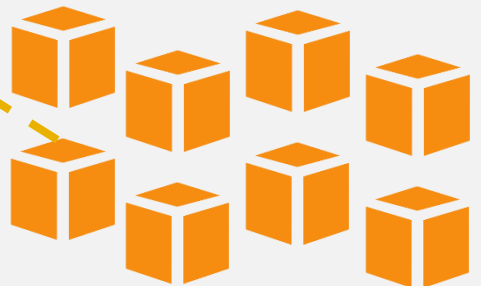
We are not announcing a single winner! We show all multi-dimensional results at cknowledge.org/dashboard/request.asplos18 and let users select best ML/SW/HW stacks depending on multiple constraints!

Other companies managed to reproduce results and started using CK

Multi-objective results for all AI/SW/HW stacks are presented on a live scoreboard and become available for public comparison and further customization, optimization and reuse!



CK assists
AWS market place
with collaboratively
optimized AI/ML stacks



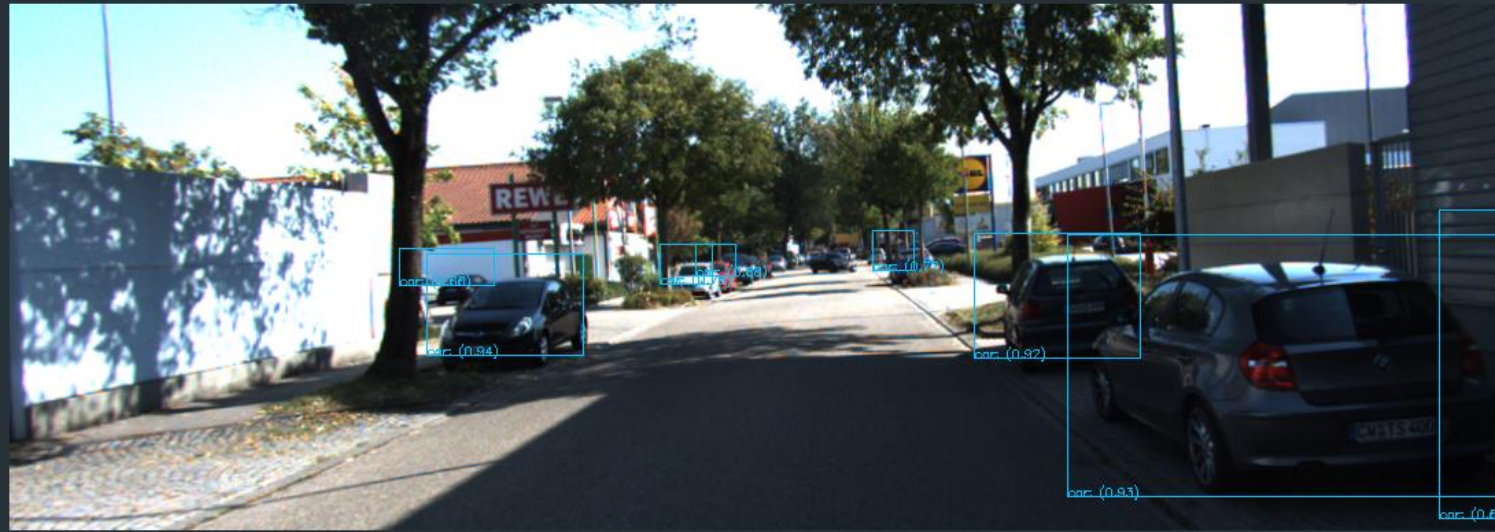
Accelerate technology transfer: companies can now quickly validate published techniques in their production environment using shared CK workflows!




See Amazon presentation at O'Reilly AI conference:

conferences.oreilly.com/artificial-intelligence/ai-eu/public/schedule/detail/71549

CK helps General Motors to select the most efficient SW/HW stacks

Collaboratively optimizing deep learning via Collective Knowledge



OBJECT	FOUND	EXPECTED	FALSE POSITIVES	PRECISION	RECALL
	8	0	8	0	0
	0	0	0	1	1
	0	0	0	1	1

MODE

Object detection

ENGINE

TensorFlow library (prebuilt, cpu)

MODEL

TensorFlow model - SqueezeDet (SqueezeDet)

IMAGE SOURCE

KITTI Drive 0009

IMAGES PER SECOND

1.19

AVERAGE PRECISION

0.67

Stop



$\vec{a} = \frac{d\vec{v}}{dt}$ dividiti.com



cknowledge.org/ai

Performance, accuracy, power consumption practically never match official reports!

CK allows to select the most efficient SW/HW stacks on a Pareto frontier (performance, accuracy, energy, memory usage, costs) for object detection, image classification and other tasks: www.youtube.com/watch?v=1ldgVZ64hEI

CK helps to automate Student Cluster competitions

github.com/ctuning/ck-scc18/wiki - proof-of-concept CK workflow
to automate installation, execution and customization of SeisSol application
from the SC18 SCC Reproducibility Challenge
across different platforms, environments and datasets

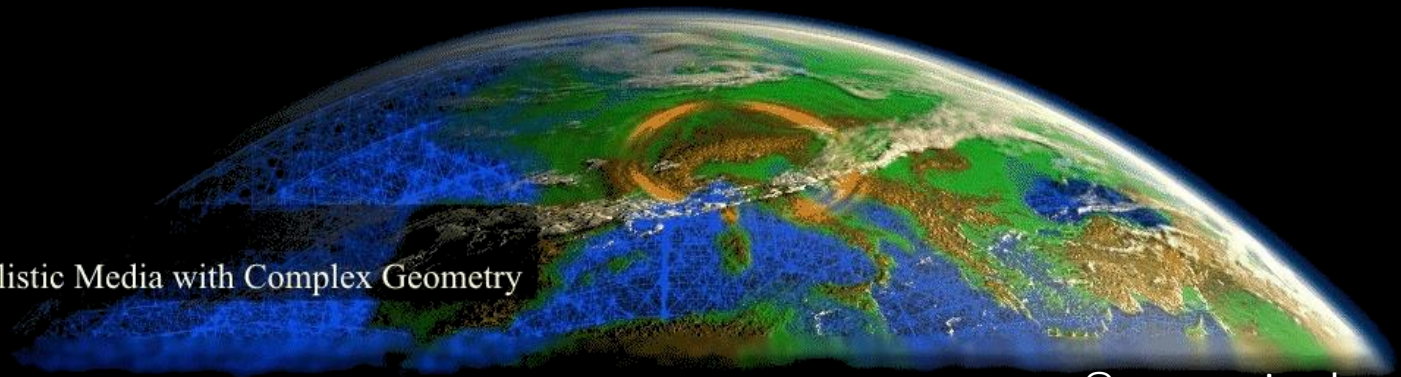
Artifact automated and reusable

Collective Knowledge COMPATIBLE

Workflow CK

SeisSol

High Resolution Simulation of
Seismic Wave Propagation in Realistic Media with Complex Geometry



© www.seissol.org

- Support automatic detection of already installed tools and data sets
- Can install missing dependencies via EasyBuild and Spack
- Can deploy application on different supercomputers with different job managers
- Can automatically validate the correctness of results (output, performance)

Technical Program

Call for Participation



Papers

March 1, 2019 – Submissions open
April 10, 2019 – Full paper deadline

Tutorials

February 15, 2019 – Submissions open
April 16, 2019 – Submissions close

Panels

February 15, 2019 – Submissions open
April 23, 2019 – Submissions close

Workshops

January 1, 2019 – Submissions open
February 14, 2019 – Submissions close

Posters

February 15, 2019 – Submissions open
July 31, 2019 – Submissions close

More Opportunities

Awards
Birds of a Feather
Early Career
Exhibitor Forum

Being part of the SC Conference enhances your career – whether you are presenting new research, showcasing innovative work or practices, helping teach the next generation, or competing for peak performance. The SC selection process is highly competitive and being selected is extremely rewarding.

Submit your work to SC19!
sc19.supercomputing.org/submit/



Program: November 17–22, 2019

Exhibits: November 18–21, 2019

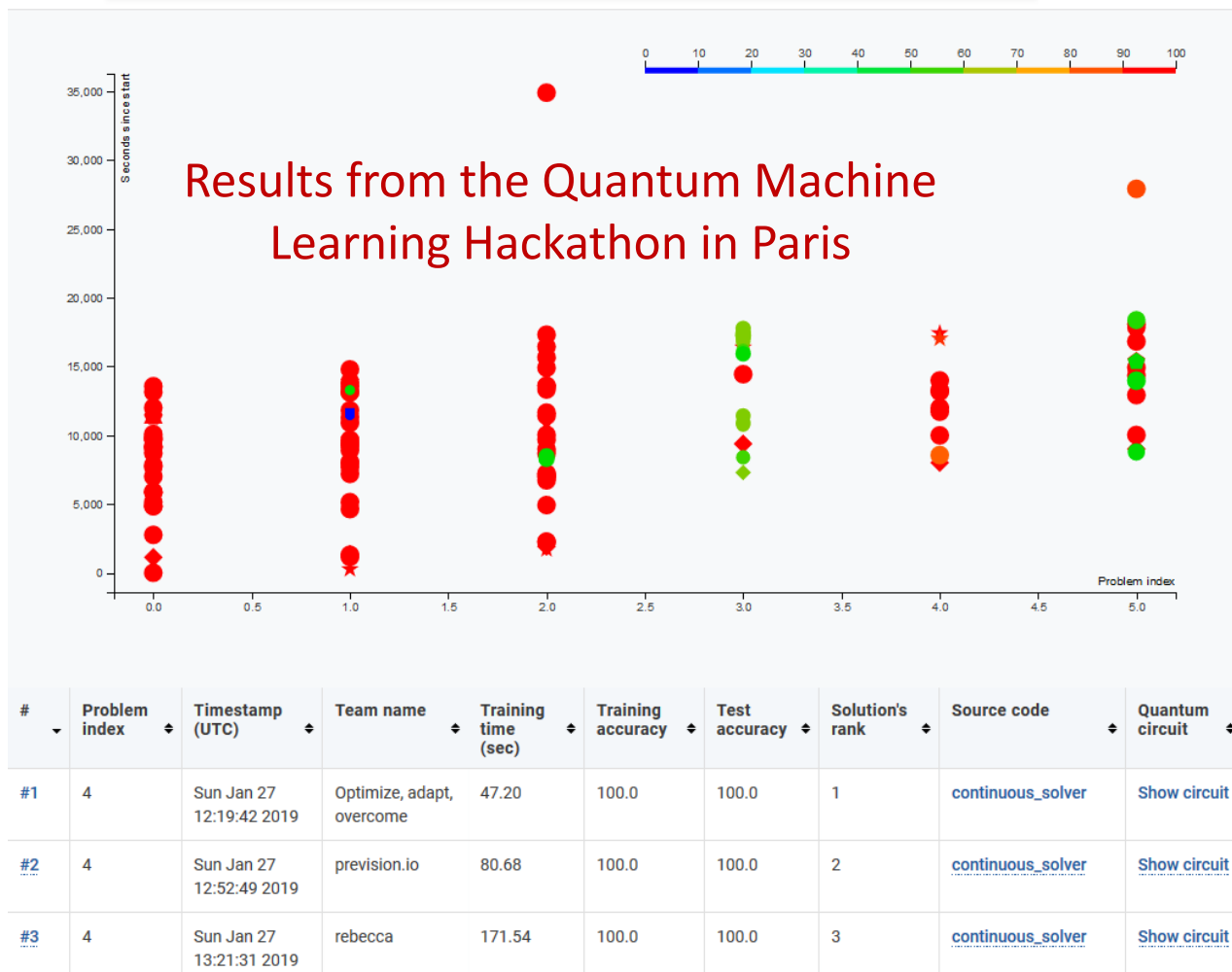
Colorado Convention Center, Denver,
CO

**The International Conference
for High Performance
Computing, Networking,
Storage, and Analysis**

CK is used to collaboratively advance quantum computing

cKnowledge.org/quantum - Quantum Collective Knowledge workflows (QCK) to support reproducible hackathons, and help researchers share, compare and optimize different algorithms across conventional and quantum platforms

cKnowledge.org/dashboard/hackathon.20190127



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

rigetti

RIVERLANE

ThoughtWorks®

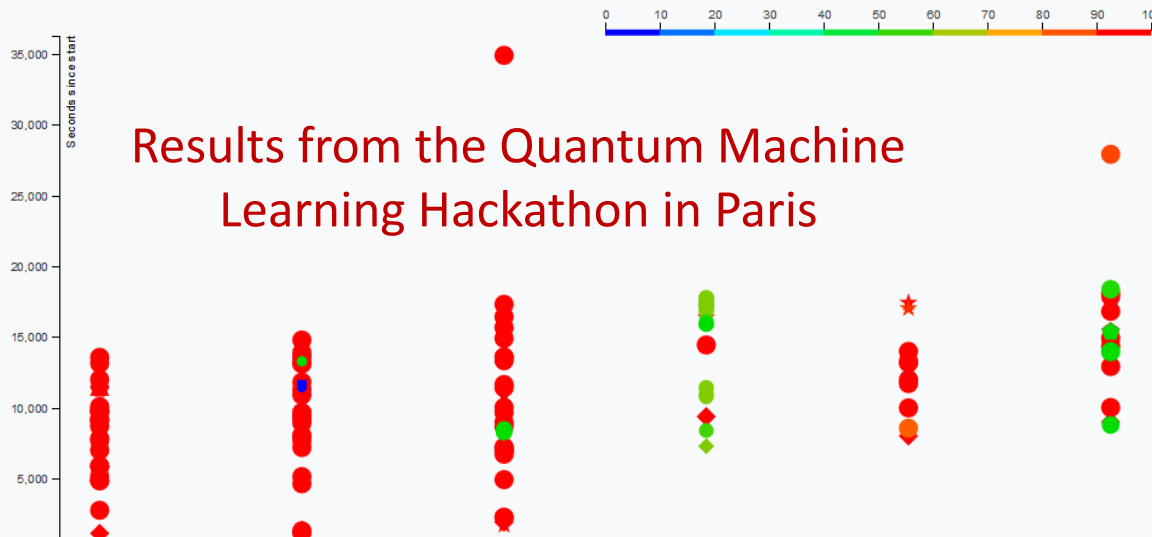
QUANTO
NATION

Innovate UK

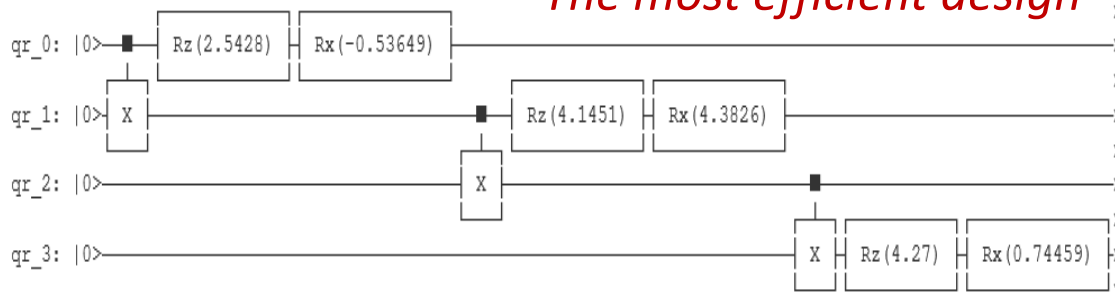
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cKnowledge.org/dashboard/hackathon.20190127



The most efficient design



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

rigetti

RIVERLANE

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QUANTO
NATION

Innovate UK

From prototype to production quality (beginning of a long journey)

- Collaboratively standardize APIs and meta descriptions
- Improve installation and documentation
- Add more CK components and workflows for real-world tasks

Open to collaboration

- Joint R&D projects and tournaments (AI, ML, quantum)
- Automation and sharing of experiments
- Reproducible articles with reusable workflows

Websites:

- github.com/ctuning/ck
- cKnowledge.org/shared-repos.html

Contact

Grigori.Fursin@cTuning.org or grigori@dividiti.com