Dynamic hybrid workflows for Deep Learning on HPC infrastructure

Iacopo Colonnelli, Assistant Professor (RTD-A) Università degli Studi di Torino Member of the CWL Technical Team







Reproducibility and FAIRness

Reproducibility

Reproducible Workflows

- Version control repositories
- Scripts / containerisation
- Recipes
- Accessible forcing data
- Attached DOIs

Standardised Assessment

- Common diagnostics
- Common code base

User/Community Value

- Publishing requirement
- Accelerate debugging & development
- Recognition for "non-standard" outputs
- Democratisation of skills
- Shared knowledge base



Reproducibility in Machine Learning

JPINEAU@CS.MCGILL.C

PHILVLAM@GMAIL.CO

BEYGEL@YAHOO-INC.COM

Improving Reproducibility in Machine Learning Research (A Report from the NeurIPS 2019 Reproducibility Program)

Joelle Pineau

School of Computer Science, McGill University (Mila) Facebook AI Research CIFAR

Philippe Vincent-Lamarre

Ecole de bibliothèconomie et des sciences de l'information,

Université de Montréal

Koustuv Sinha

KOUSTUV.SINHA@MAIL.MCGILL.C

School of Computer Science, McGill University (Mila)

 $Facebook\ AI\ Research$

Vincent Larivière

VINCENT.LARIVIERE@UMONTREAL.C.

FLORENCE.DALCHE@TELECOM-PARIS.FR

 $Ecole\ de\ biblioth\'e conomie\ et\ des\ sciences\ de\ l'information,$

Université de Montréal

Alina Beygelzimer

Yahoo! Research

Florence d'Alché-Buc

Télécom Paris,

 $Institut\ Polytechnique\ de\ France$

Emily Fox

University of Washington

Apple

Hugo Larochelle

Google CIFAR

HUGOLAROCHELLE@GOOGLE.COM

EBFOX@CS.WASHINGTON.EDU

A Step Toward Quantifying Independently Reproducible Machine Learning Research

Edward Raff

Booz Allen Hamilton

The Thirty-Second AAAI Conference on Artificial Intelligence (AAAI-18)

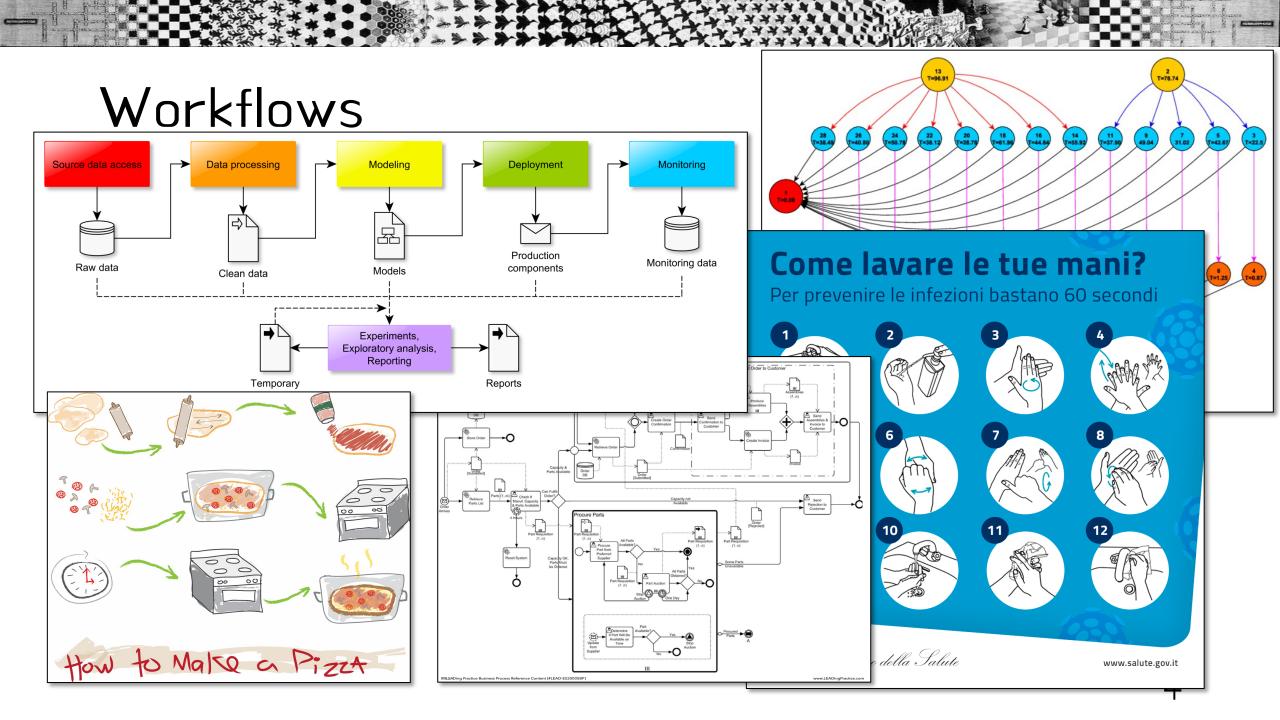
State of the Art: Reproducibility in Artificial Intelligence

Odd Erik Gundersen, Sigbjørn Kjensmo

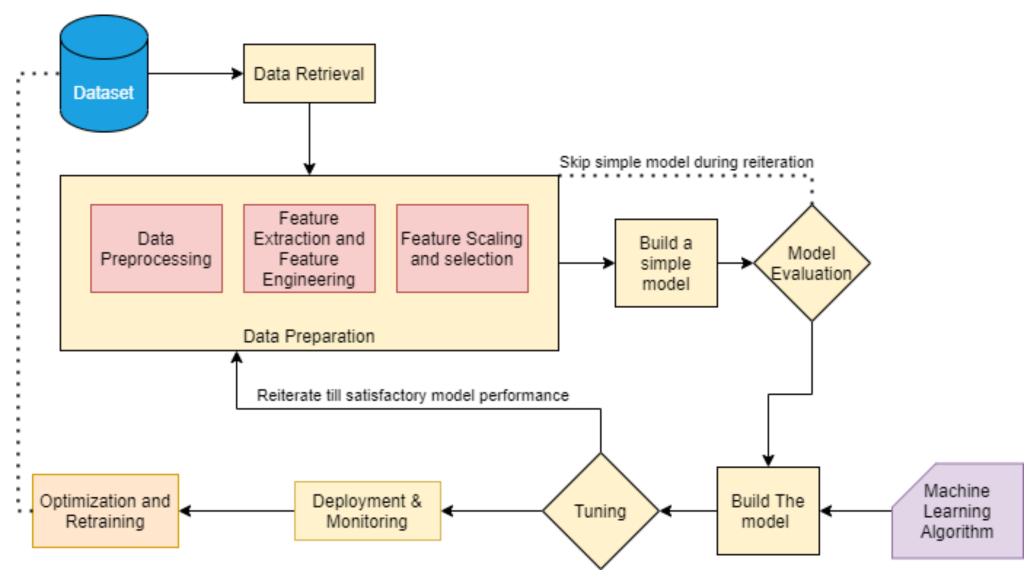
Department of Computer Science Norwegian University of Science and Technology



A workflow is an abstraction that models a complex and modular working process as a set of steps and their inter-dependencies.



Workflows





- Host semantics define the subprogram in each workflow step, usually expressed in a general-purpose programming language (e.g., Java, Python, C++) or as a shell script
- Coordination semantics define the interactions between steps.
 Coordination semantics can be either interleaved with host semantics or expressed through a declarative markup syntax, an imperative Domain Specific Language (DSL), or a graph-based modelling interface

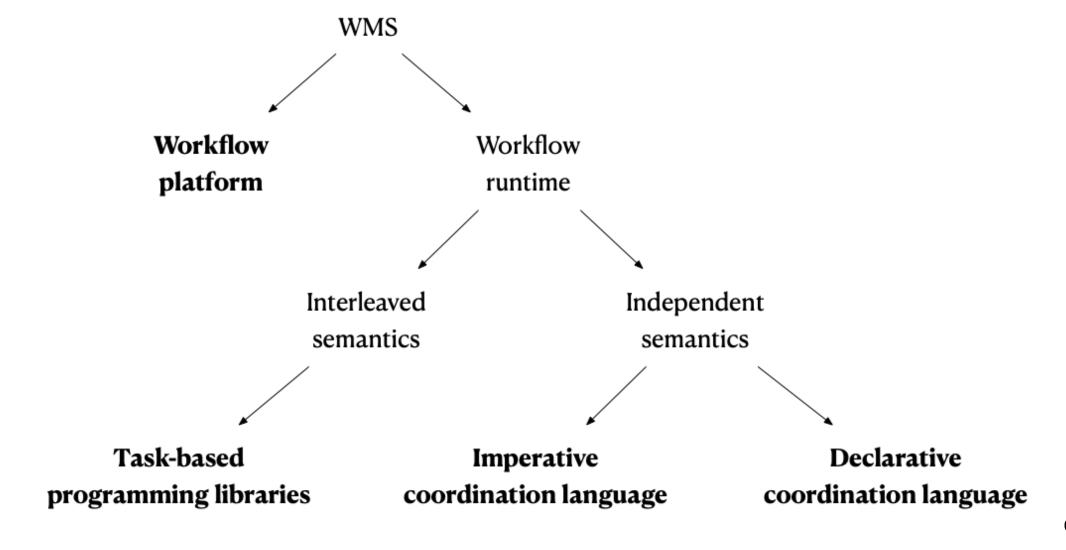


- During the design phase, a domain expert describes the different functional components of an application and their dependencies as a workflow model
- During the runtime phase, a WMS deploys and manages the computational units required for the workflow execution



Tools in charge of exposing coordination semantics to the users and orchestrating workflows

Workflow Management Systems (WMSs)





- Support both design and runtime phases, usually through advanced Graphical User Interfaces (GUI)
- Support all aspects of workflow management, e.g., provenance collection, catalogs, and fault-tolerance
- Usually tightly coupled with a specific underlying architecture (e.g., the Grid), without focusing on portability
- They are usually complex to be installed and properly configured, as they rely on low-level external libraries that must be independently managed (e.g., HTCondor or GAP interface)

Workflow Platforms







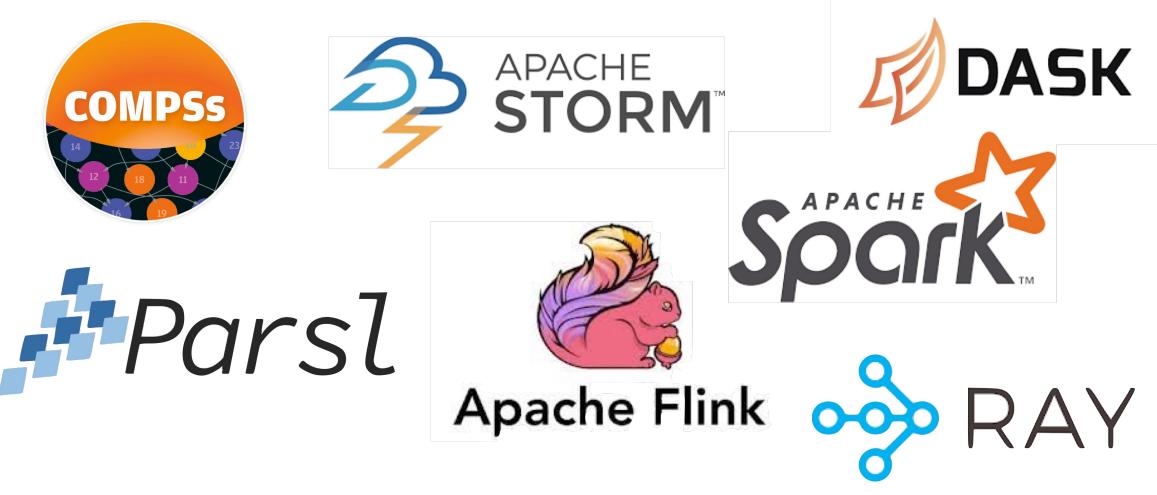






- Users identify and annotate functions that can be executed as asynchronous remote tasks
- Synchronicity is typically implemented with the futures paradigm
- The workflow execution plan, typically a layered dataflow model, is **built just-in-time** by the runtime engine
- Privilege performance over accessibility, exposing a low-level programming model directly to the user
- Task-based programming libraries commonly offer support for a limited set of host languages, resulting in limited reusability and extensibility

Task-based Programming Libraries



Imperative Coordination Language

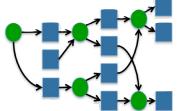
- Workflow are described using an imperative DSL, which is commonly a subset of a general-purpose programming language
- Apache Airflow and Snakemake are essentially Python scripts extended by declarative code that can be executed on distributed infrastructures
- Makeflow exposes a technology-neutral syntax similar to Make
- The Nextflow framework builds on the Unix pipe concept to expose an explicit dataflow model
- Toil and DagOnStar model workflows as pure Python scripts, through dedicated APIs

Imperative Coordination Language



Massively Parallel Workflows (and fire-breathing dragon slugs)





Declarative Coordination Language

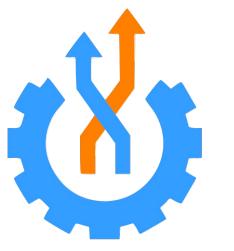
- The Common Workflow Language (CWL) is an open standard for describing workflow DAGs following a JSON or YAML syntax
- Other examples of workflow modelling open standards are the Workflow Description Language (WDL) and the Serverless Workflow Specification
- Declarative coordination languages are commonly less expressive than imperative ones, but it's easier for WMSs to apply rewriting techniques for optimization, improving performance portability
- Also, declarative languages are usually product-agnostic, improving portability and reusability. An exception is DAX, the Pegasus' XML-based low level representation of DAGs

Declarative Coordination Language









Serverless Workflow Specification

Common Workflow Language (CWL)



- Open standard for describing analysis workflows and tools
- Defined with a schema, specification and test suite
- Portable and scalable across a variety of software and deployment environments
- Designed to meet the needs of dataintensive science to improve the FAIRness of their workflows







Common Workflow Language (CWL)

• Human readable (YAML or JSON)

• CWL file contains a CommandLineTool or Workflow description

```
cwlVersion: v1.2
class: CommandLineTool

baseCommand: echo

inputs:
    message_text:
    type: string
    inputBinding:
        position: 1

outputs: []
```

```
rsion: v1.2
class: Workflow
inputs:
  rna reads fruitfly: File
steps:
 quality control:
    run: bio-cwl-tools/fastqc/fastqc_2.cwl
    in:
      reads_file: rna_reads_fruitfly
    out: [html file]
outputs:
 quality_report:
   type: File
   outputSource: quality_control/html_file
```

Common Workflow Language (CWL)

- Human readable (YAML or JSON)
- CWL file contains a CommandLineTool or Workflow description

cwlVersion: v1.2

• Inputs/outputs are explicitly stated





- CWL Types: strings, numbers, files, or records that combine these; or arrays of any of these types
- Union and optional types too

```
cwlVersion: v1.2
class: CommandLineTool

baseCommand: echo

inputs:
    message_text:
    type: string
    inputBinding:
    position: 1

outputs: []
```

```
inputs:
    rna_reads_fruitfly File

message_text: Hello world!

Implicit string type
```

```
cwlVersion: v1.2
class: Workflow
inputs:
  rna_reads_fruitfly: File
steps:
  quality_control:
    run: bio-cwl-tools/fastqc/fastqc_2.cwl
    in:
      reads_file: rna_reads_fruitfly
    out: [html file]
outputs:
 quality_report:
    outputSource: quality_control/html_file
```



```
#!/usr/bin/env cwl-runner
cwlVersion: v1.2
class: Workflow
requirements:
  ScatterFeatureRequirement: {}
inputs:
  message_array: string[]
steps:
  echo:
    run: hello_world.cwl
    scatter: message
    in:
      message: message_array
    out: []
outputs: []
```

CWL Supports *Scatter/Gather* parallel patterns at the step level since v1.0.

If scatter declares more than one input parameter, scatterMethod describes how to decompose the input into a discrete set of jobs (dotproduct, nested crossproduct, or flat crossproduct).



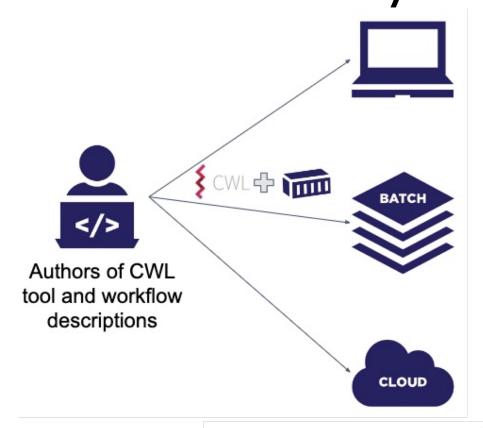
```
#!/usr/bin/env cwl-runner
cwlVersion: v1.2
class: CommandLineTool
baseCommand: node
hints:
  DockerRequirement:
    dockerPull: node:slim
inputs:
  src:
    type: File
    inputBinding:
      position: 1
outputs:
  example out:
    type: stdout
stdout: output.txt
```

CWL Supports *software containers* at the CommandLineTool level since v1.0.

The DockerRequirement directive allows users to specify the Docker image that should execute the command

Multiple CWL implementations can support different container runtimes

CWL Portability











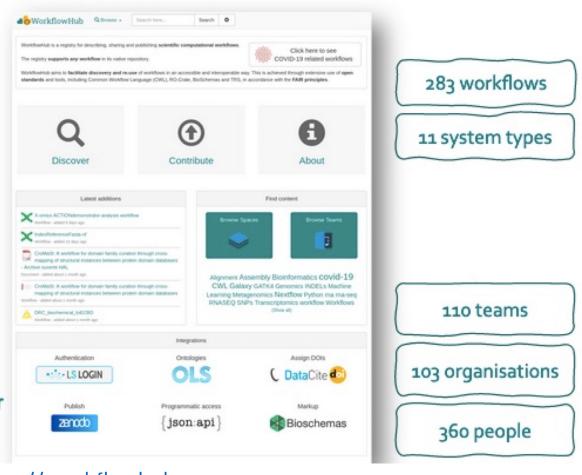
CWL Ecosystem - CWL Viewer



https://view.commonwl.org

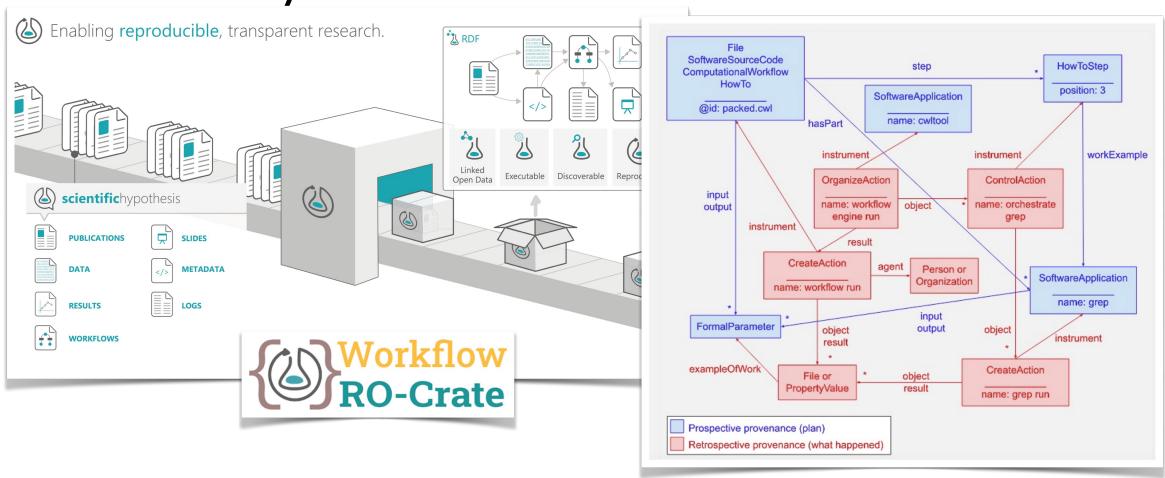
CWL Ecosystem - WorkflowHub





https://workflowhub.eu

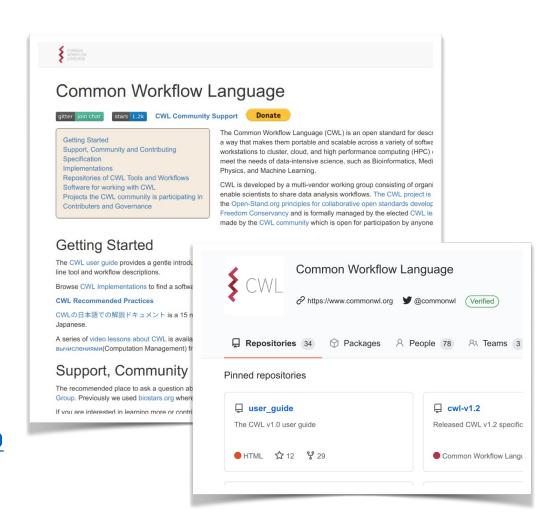
CWL Ecosystem - Workflow Run RO-Crate



https://www.researchobject.org/workflow-run-crate/

CWL Community

- Website: https://www.commonwl.org/
- User guide: <u>https://www.commonwl.org/user_guide/</u>
- Forum: https://cwl.discourse.group/
- Chat: https://matrix.to/#/#cwl:matrix.org
- GitHub: https://github.com/common-workflow-language/
- Weekly video chat: <u>https://groups.google.com/forum/#!forum/common-workflow-language-videochat-invites</u>







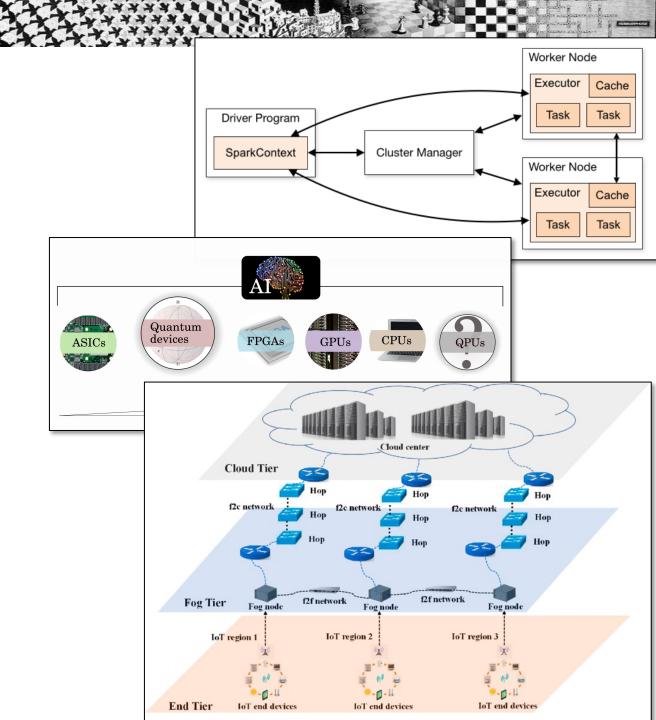
https://github.com/Sera91/SMR3941-ICTP/blob/main/Day2/Tutorial-Workflow/README.md

Hybrid workflows

Scientific Workflows

CHALLENGES:

- Each step of a distributed application can require multiple intercommunicating agents (e.g., a Spark cluster or a microservices architecture);
- Large-scale architectures can be heterogeneous (e.g., Cloud+HPC environments and Classical+Quantum computing);
- Large-scale architectures can be modular, and modules can be independent of each other (e.g., modular HPC and infrastructure federations)



Hybrid Workflows

Workflow model

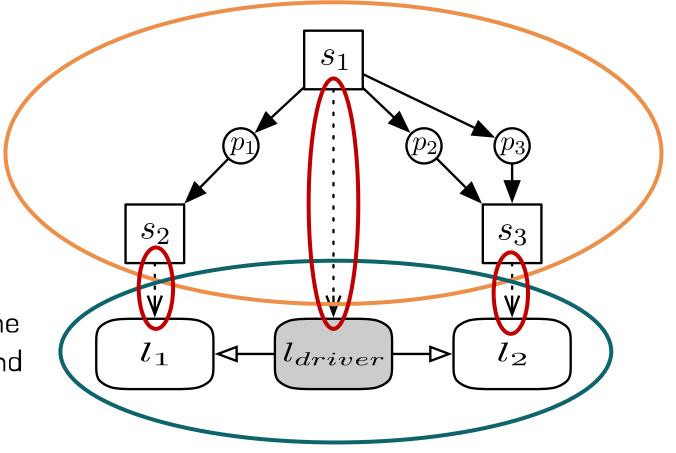
A directed bipartite graph encoding executable steps, data ports and dependencies between them

Topology of deployment locations

A directed graph where the nodes are the locations in charge of executing steps and the links are directed communication channels between locations

Mapping relations

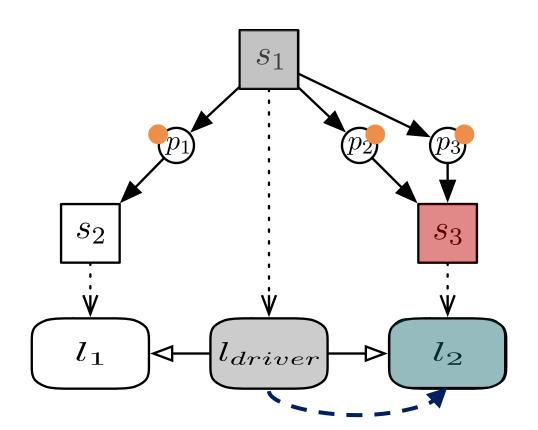
Many-to-many relations stating which locations are in charge of executing each workflow step



Model Interpretation

A step s becomes fireable (ready for execution) when:

- Each input port In(s) contains the right number of tokens
- Its related location is deployed
- All its input data have been transferred on that location



The StreamFlow WMS

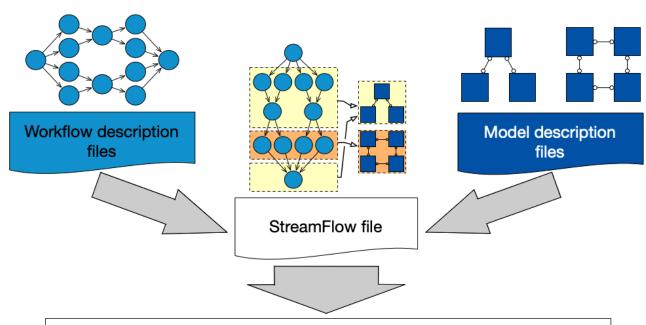


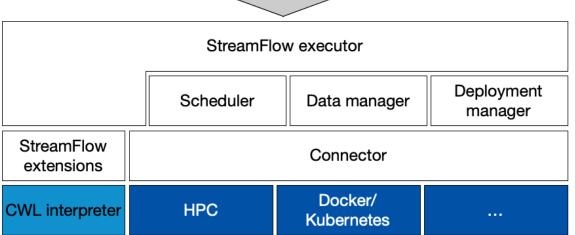




https://streamflow.di.unito.it

I. Colonnelli, B. Cantalupo, I. Merelli and M. Aldinucci, "StreamFlow: cross-breeding cloud with HPC," in *IEEE Transactions on Emerging Topics in Computing*, vol. 9, iss. 4, p. 1723-1737, 2021. doi: 10.1109/TETC.2020.3019202.







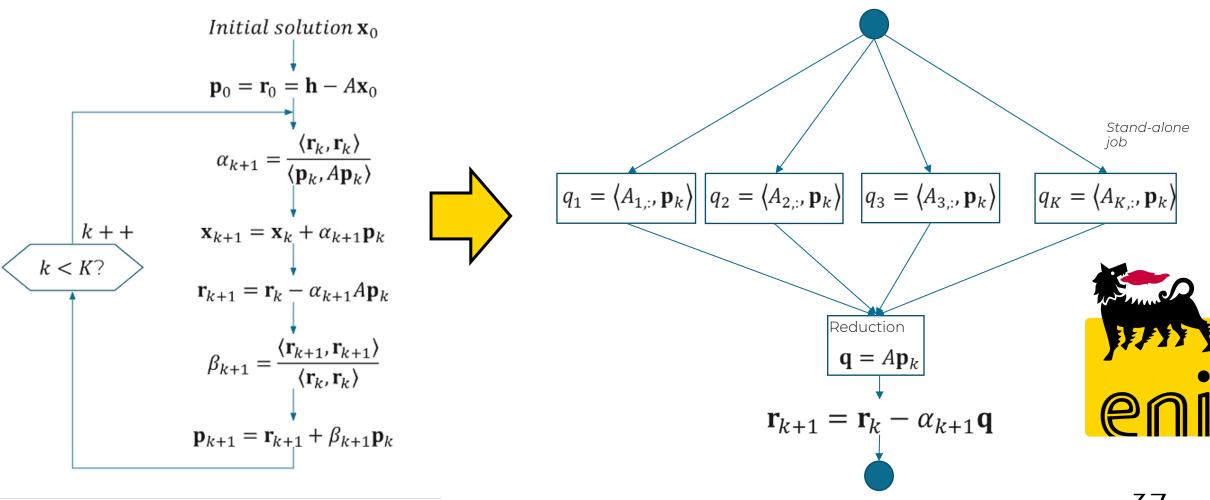


The StreamFlow WMS

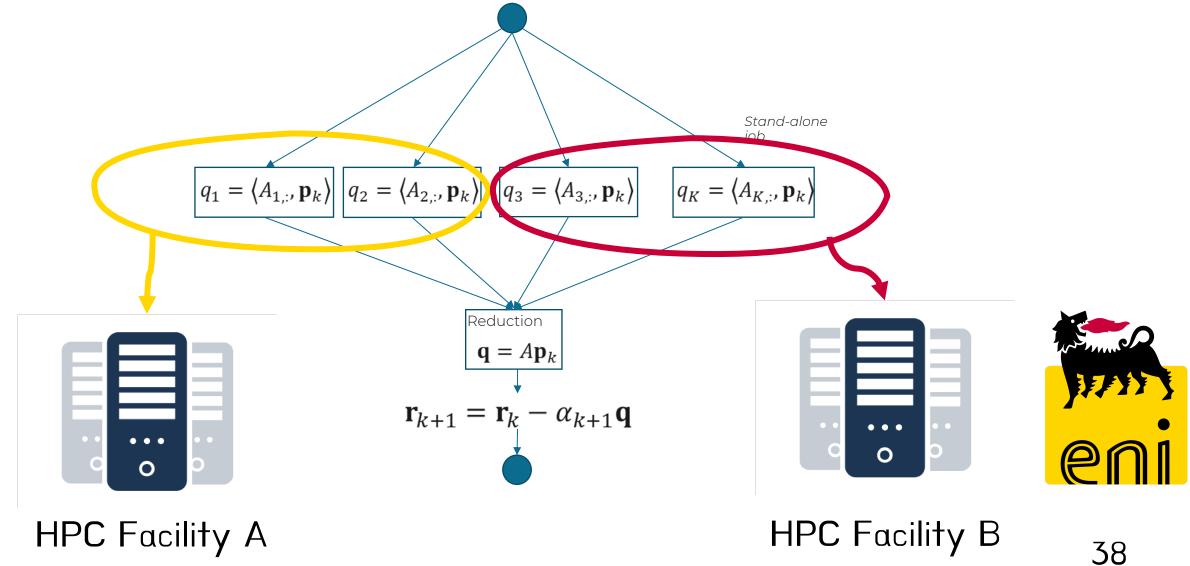
StreamFlow is listed as a production-ready implementation of CWL. It has also been used as a software laboratory to experiment new CWL extensions in the CWL4HPC Working Group (e.g., the Loop extension for iterative workflows)

Software	Description	Self-Reported Compliance	Platform support
cwltool	Reference implementation of CWL	CWL v1.0 - v1.2	Linux, OS X, Windows, local execution only
<u>Arvados</u>	Distributed computing platform for data analysis on massive data sets. <u>Using CWL on Arvados</u>	CWL v1.0 - v1.2 required 100%	AWS, GCP, Azure, Slurm, LSF
<u>Toil</u>	Toil is a workflow engine entirely written in Python.	CWL v1.0 - v1.2	AWS, Azure, GCP, Grid Engine, HTCondor, LSF, Mesos, OpenStack, Slurm, PBS/Torque
CWL-Airflow	Package to run CWL workflows in Apache-Airflow (supported by BioWardrobe Team, CCHMC)	CWL v1.0 - v1.1	Linux, OS X
StreamFlow	Workflow Management System for hybrid HPC-Cloud infrastructures	CWL v1.0 - v1.2 required 100% (and nearly all optional features)	Kubernetes, HPC with Singularity (PBS, Slurm), Occam, multi-node SSH, local-only (Docker, Singularity)

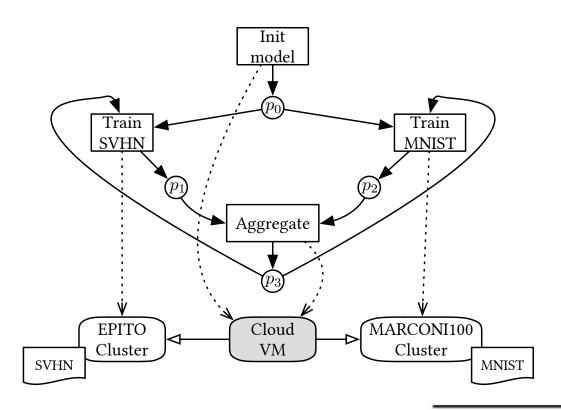
Case study: Distributed Conjugate Gradient



Case study: Distributed Conjugate Gradient



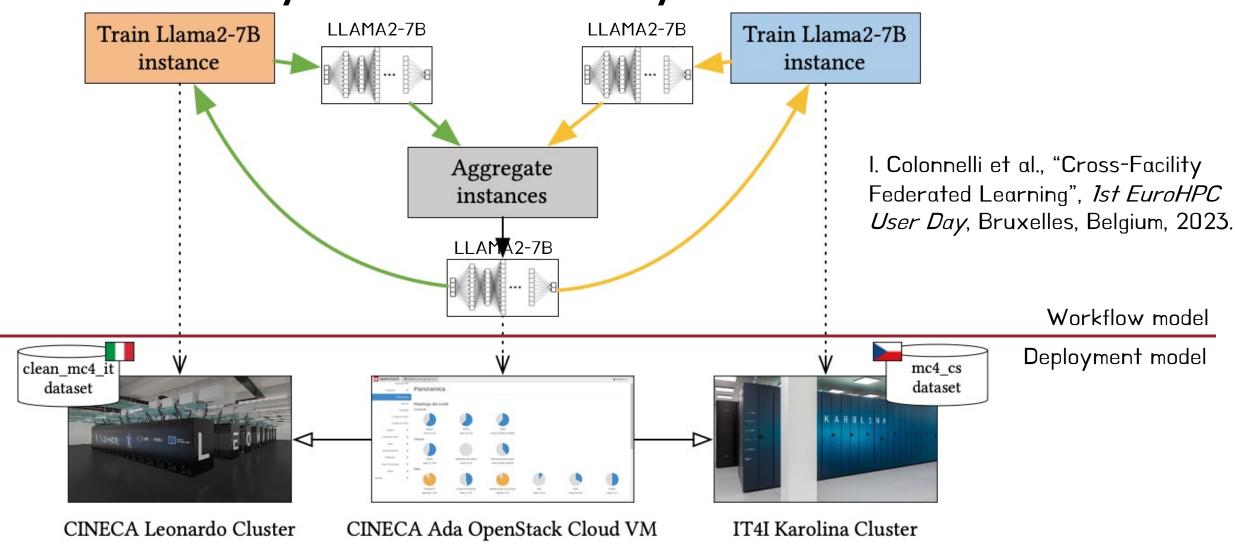
Case study: Cross-Facility Federated Learning



I. Colonnelli, B. Casella, G. Mittone, Y. Arfat, B. Cantalupo, R. Esposito, A. R. Martinelli, D. Medić and M. Aldinucci, "Federated Learning meets HPC and cloud," in *Astrophysics and Space Science Proceedings*, vol 60, 2023, p. 193–199. doi: 10.1007/978-3-031-34167-0_39

		StreamFlow			OpenFL		
		MNIST acc.	SVHN acc.	Time	MNIST acc.	SVHN acc.	Time
Cloud	100 rounds, 1 epoch/round 50 rounds, 2 epochs/round	99.36% 99.37%		2h40m 2h20m	97.91% 98.88%	93.15% 94.21%	3h06m 2h09m
Hybrid	100 rounds, 1 epoch/round 50 rounds, 2 epochs/round	99.29% 99.34%	93.06% 92.85%	2h57m 1h45m	_	_	_

Case study: Cross-Facility Federated Learning



Literate workflows



CHALLENGES:

- Learning a new coordination language is an extra efforts that often domain experts don't do;
- Dealing with language syntax and semantics (although simple and declarative) can be difficult for non IT people;
- People are often more comfortable in extending their knowledge of a product they already use, instead of learning something new from scratch.

Computational Notebooks

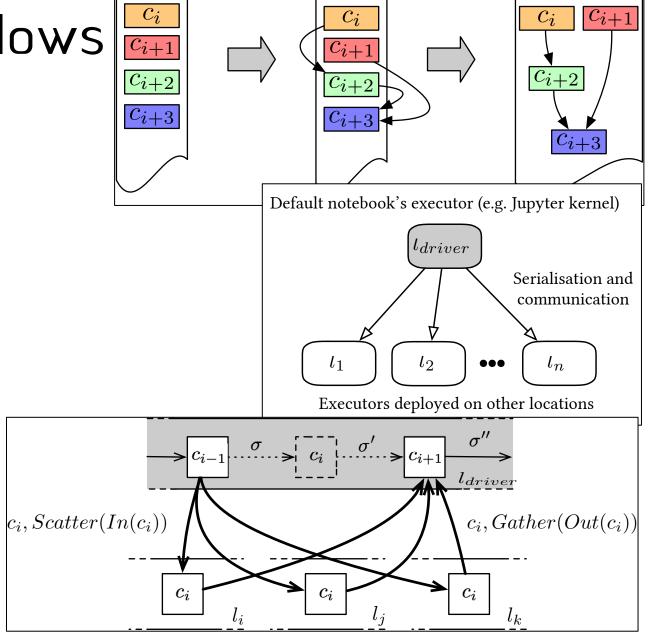
CHALLENGES:

- Notebooks' purely sequential execution flow makes it impossible to exploit the inherent concurrency of workflow graphs;
- The lack of a rigorous workflow model prevents to satisfy nonfunctional requirements like portability, reproducibility, provenance collection;
- Using Notebooks as a high-level interface to HPC facilities poses crucial **security challenges** due to the lack of support for hybrid topologies.

Hybrid Literate Workflows

REQUIREMENTS:

- Infer inter-cell true data dependencies to construct a DAG
- Derive sequentially equivalent parallel semantics to extract concurrency from the cells execution;
- Extend the Notebook metadata format to describe:
 - Topologies of deployment locations
 - Mapping relations
 - Explicit intra-cell data-parallel constructs (e.g. scatter/gather)

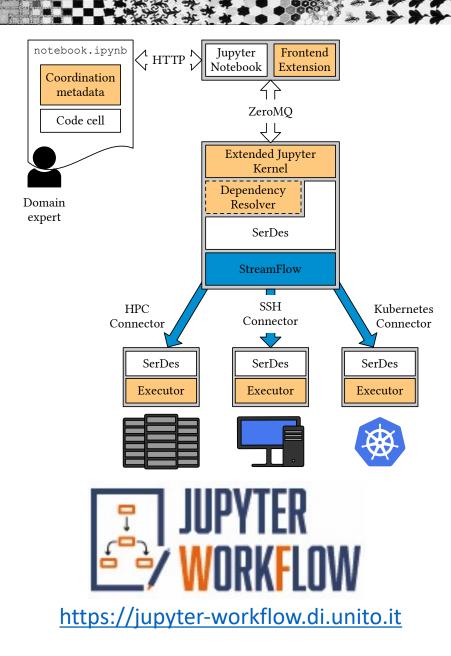




The Jupyter Workflow kernel extends the IPython software stack to support hybrid literate workflows in the Jupyter stack.

It consists of three main components:

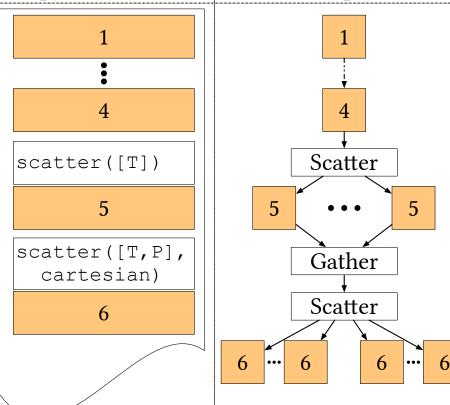
- A coordination metadata format to model global cells configurations and location topologies;
- A dependency resolver component to help users identify the input dependencies of each cell;
- A Jupyter stack extension to handle coordination metadata, execute cells remotely and manage data transfers (through StreamFlow).

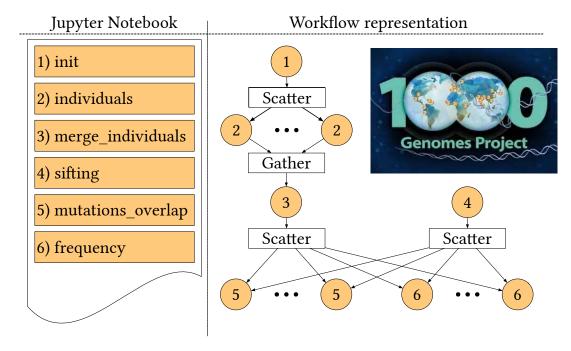


```
DOSSIER Scatter Demo Last Checkpoint: 06/20/2022 (autosaved)
                                                                                    Edit Workflow Step
                                                               V 🔳 🌣 Edit Workflow 🗴
                                                                                    Configuration
                                                                                    In [1]:
                            import time
                                                                                    Inputs
                           var = [1, 2, 3, 4, 5]
start = time.perf_counter()
                                                                                    Automatically infer input dependencies
                                                                                     print var str time
                    In [2]:
                            for i in var:
                                                                                     Input name
                               print("Processing variable " + str(i))
                               time.sleep(5)
                                                                                    Scatter
                            Processing variable 1
                            Processing variable 2
                            Processing variable 3
                                                                                     1 {
                            Processing variable 4
                                                                                         "items": [
                            Processing variable 5
                                                                                           "var"
                                                                                    4 ]
5 }
                    In [3]:
                                                                                    Outputs
# Workflow metadata
                                                                                     Output name
 "step": {
   "in": [{ # List the members of In(c_i)
                                                                                    Target
        "type": "name" | "env" | "file" | "control",
        "name": "variable name",
                                                                                    Deployment
        "serializer": {
                                                                                     Local Process
            "predump": "code executed before serializing",
                                                                                    Locations
            "postload": "code executed after serializing"
        "value": "value to assign to the name",
        "valueFrom": "can take value from a different variable"
   }],
    "autoin": True | False, # Resolve In(c_i) automatically
    "out": [ # List the members of Out(c_i)
   ],
    "scatter": {
        "items": ["variable name" | "scatter subscheme"],
        "method": "dotproduct" | "cartesian" | ...
 },
```

Jupyter Workflow

Jupyter Notebook | Workflow representation





I. Colonnelli, M. Aldinucci, B. Cantalupo, L. Padovani, S. Rabellino, C. Spampinato, R. Morelli, R. Di Carlo, N. Magini, and C. Cavazzoni, "Distributed workflows with Jupyter," *Future generation computer systems*, vol. 128, pp. 282-298, 2022.

https://jupyter-workflow.di.unito.it