## column fow

CLUSTER OF EXCELLENCE
QUANTUM UNIVERSE

# columnflow: Fully automated analyses via flow of columns over distributed resources 

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ACAT 2024
15.3.2024

General idea

- Python-based framework for nano-like inputs
- End-to-end orchestration \& automation
- No reliance on single local cluster or local storage
- Adapt to any remote cluster and storage system
- HTCondor, Slurm, CMS-CRAB, LSF
- Store via file://, xrootd://, gsiftp://, webdav://
- Persistent intermediate outputs
- Debugging, reuse, sharing across groups

Key concepts

- Experiment agnostic core
- Organize experiment-specific recipes in extensions
- Use awkward arrays as interface, parquet as file format
- Give users full control over processing tools
(NumPy, TensorFlow, coffea-nano-format, pandas, ...)
- High degree of code-reuse and collaboration
- Define workflows with luigi + law, metadata with order
- Control and execution via CLI, scripts and notebooks

Automation stack


Example graph*

Parallelization over

- Campaigns \& datasets
- Files
- Systematics
- Typically $\mathcal{O}(10 \mathrm{k}) 60 \mathrm{~min}$
jobs, however, on standard resources standard resource
$\checkmark$ HTCondor, CRA
Graph execution
- Single command can trigger the full pipeline from inputs to plots
- Example


Documentation
O github.com/columnflow

Simple customization

- Provide simple functions producers, to create
- calibrated (updated) columns
- selection mask
- ML training \& evaluatio - variables
- Nesting enables for easy reuse and capsulation


## General idea

- Python-based framework for nano-like inputs
- End-to-end orchestration \& automation $\triangleright$ From events to plots in a single command
- No reliance on single local cluster or local storage
- Adapt to any remote cluster and storage system
$\triangleright$ HTCondor, Slurm, CMS-CRAB, LSF
■ Store via file://, xrootd://, gsiftp://, webdav://
- Persistent intermediate outputs
$\triangleright$ Debugging, reuse, sharing across groups


## Key concepts

- Experiment-agnostic core
- Use awkward arrays as interface, parquet as file format
- Give users full control over tools used (NumPy, TensorFlow, coffea-nano-format, pandas, ...)
- Define workflows with luigi + law, metadata with order
- Capsulation of standard recipes
- High degree of code-reuse \& collaboration


## Automation stack

国 docs
( ) repo
workflow engine (originally by Spotify)
luigi analysis workflow
layer for HEP \& scale-out
(experiment independent)


## Example graph

Just a suggestion, can be easily altered or amended by analyses

## Nano inputs -----.--

## Simple customization

- Provide simple functions, producers, to create
- calibrated (updated) columns
- selection masks
- new columns
- ML training \& evaluation
- variables
- Nesting enables for easy reuse and capsulation


## @producer!

uses $\{$ inuuon", "Muon. pt", "Muon.eta",
\},
produces $\{$
\}, "muon_weight", "muon_weight_up", "muon_weight_down",
\}, "muon_weight", "m
\# only allowed
mc_only True,
def muon_weights(
self: Producer,
events: ak-Array,
events: ak.Array,
moon mask: ak.Array | type(Ellipsis) = Ellipsis,
tskwargs,
) -> ak.Arraray:
-> ak.Array:
."."
© Creates muon weights using the correctionlib. m"
"

pt = flat_np_view(events.Muon.pt [muon_mask], axis-1)
loop over systematics
syst, postfix in
syst, posttix
("sf", ""),

sf_flat = self.muon_sf_corrector(self.year, abs_eta, pt, syst)
\# add the correct layout to it
sf $=$ layout_ak_array(sf_flat, events.Muon.pt [muon_mask])
\# create the product over all muons per event
weight $=$ ak.prod(sf, axis-1, mask_identity False)
events = set_ak_column (events, f"muon_weight\{postfix\}", weight,

Plots \& results $\qquad$


## Example graph

Just a suggestion, can be easily altered or amended by analyses

## Nano inputs -------

## Simple customization

- Provide simple functions, producers, to create
- calibrated (updated) columns
- selection masks
- new columns
- ML training \& evaluation
- variables
- Nesting enables for easy reuse and capsulation


## Graph execution

- Single command can trigger the full pipeline from inputs to plots, or any intermediate task
- Example
law run cf.PlotVariables1D \}
--version dev1 \}
--datasets ttbar,dy
--calibrators jec,jer \}
--selector full \}
--producers muon_weights
--variables jet*_\{eta,pt\} \}
--workflow \{crab,htcondor, ...\}

Plots \& results $\qquad$


Backup
columnflow in depth

- Python framework for vectorized, columnar HEP analysis with flat (nano-like) inputs
- Mostly experiment agnostic core, plenty of CMS-related specializations on top
- Using awkward arrays + coffea nano-scheme, parquet as file format
- Workflows with luigi/law, metadata definition using order
- Our initial wishlist
- End-to-end orchestration \& automation - One command can trigger the entire workflow
- Highly parallel execution on any remote batch system - HTCondor, Slurm, LSF, WLCG, CMS-CRAB, ...
- Seamless integration of any remote storage system
- Storage: file://, xrootd://, gsiftp://, webdav://, ...
- No reliance on custom, local hardware
$\triangleright$ We need to be able to invite external collaborators
$\triangleright$ Reduction in speed (!) to be compensated with high parallelism
- Persistent intermediate outputs
- Easy reuse across groups, ML applications, working with students ...


Operations

- Extension
- Selection (creating masks)
- Reduction (applying masks)
- Extension
- Merge


## $\longmapsto$ Columns $\longrightarrow$



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## $\longmapsto$ Columns $\longrightarrow$



Operations

- Extension
$\downarrow$ Selection (creating masks)
- Reduction (applying masks)
- Extension
- Merge



## Operations

$凶$ Extension
$\downarrow$ Selection (creating masks)
$\downarrow$ Reduction (applying masks)

- Extension
- Merge



## Operations

Extension
$\downarrow$ Selection (creating masks)
$\downarrow$ Reduction (applying masks)
$凶$ Extension

- Merge



## Operations

Extension
$\downarrow$ Selection (creating masks)
$\downarrow$ Reduction (applying masks)
$\checkmark$ Extension
$\star$ Merge


## Operations

$\checkmark$ Extension
$\downarrow$ Selection (creating masks)
$\downarrow$ Reduction (applying masks)
$\downarrow$ Extension
$\star$ Merge

- In-memory
- Trivial
- NumPy / awkward array provide all necessary tools and helpers
- Across a large scale analysis with persistent intermediate files
－In－memory
－Trivial
－NumPy／awkward array provide all necessary tools and helpers
－Across a large scale analysis with persistent intermediate files
－田 represent input files
－Typically $\mathcal{O}(1 k-10 k)$
$\triangleright$ High parallelism，only single－core requirement
$\triangleright$ Chunked reading with IO offloading to threads
－日 and 日 represent columns，potentially stored in additional files and same event order
－Flexible decisions by analyses whether to store columns and when to load them
－Can be written \＆read in multi－threaded IO
$\triangleright$ Only write merged $⿴ 囗 十$ when necessary
- 1 Fully orchestrated workflow
- Only a suggestion, but able to model majority of analyses
- Can be altered or created from scratch by analyses

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- 3 Collection of standardized column producers (CMS)
- Mostly SF and weight production using correctionlib $\rightarrow$ jec, jer, tec, e_sf, mu_sf, trigger_sf, btag_sf, ...
- Plug-in mechanism for analyses
- 1 Fully orchestrated workflow
- Only a suggestion, but able to model majority of analyses

live task graph


## Single producer

## Nested producer

```
@producer!
    uses={
    },
        "muon_weight", "muon_weight_up", "muon_weight_down",
    },
        only allowed on-m
    mc_only=True,
def muon_weights(
    self: Producer,
    muon_mask: ak.Array | type(Ellipsis) = Ellipsis,
        type(Ellipsis) = Ellipsis,
) -> ak.Array
        mCreates muon weights using the correctionlib.
        abs_eta = flat_np_view(abs(events.Muon.eta[muon_mask]), axis=1)
        pt = flat_np_view(events.Muon.pt[muon_mask], axis=1)
    # loop over systematic
        syst, postfix
        ("s+","),'"up"),
        ("systdown","_down"),
    ]:
    sf_flat = self.muon_sf_corrector(self.year, abs_eta, pt, syst)
    sf = layout_ak_array(sf_flat, events.Muon.pt[muon_mask])
    # create the product over all muons per event 
    events = set_ak_column(events, f"muon_weight{postfix}", weight, value_type=np.float32)
    events
```

```
@producer(
    uses={
        category_ids, features, normalization_weights, normalized_pdf_weight,
        tau_weights, electron_weights, muon_weights, trigger_weights,
    },
        category_ids, features, normalization_weights, normalized_pdf_weight,
        normalized_murmuf weight, normalized_pu_weight, normalized btag_weights,
        tau_weights, electron_weights, muon_weights, trigger_weights,
},
def default(self: Producer, events: ak.Array, **kwargs) -> ak.Array:
    events = self[category_ids](events, **kwargs)
    events = self[features](events, **kwargs)
    # mC-only weights
        self.dataset_inst.is_mc:
    events = self[normalization_weights] (events, **kwargs)
    events = self[normalized_pdf_weight](events, ** kwargs)
    # normalized renorm./fack_weivi
    events = self[normalized_murmuf_weight](events, *kwargs)
    # normatized pu weights 
    events = self[normalized_btag_weights](events, **kwargs)
    events = self[tau_weights] (events, ***wargs)
    events = self[electron_weights](events, **kwargs)
    # muon weight
    events = self[muon_weights] (events, **kwargs)
    events = self[trigger_weights](events, **kwargs)
        events
```


## 12 flow of columns




- Columns are
- produced on demand
- read only if required
- overlayed \& aliased to mimic coherent array !

- Columns are
- produced on demand
- read only if required
- overlayed \& aliased to mimic coherent array !

- Columns are
- produced on demand
- read only if required
- overlayed \& aliased to mimic coherent array !
- Existing columns
- are not reproduced
columns merged! only in memory for histogramming


E


- can be shared across groups
- NB
- Task $\neq$ jobs $\rightarrow$ jobs can run multiple tasks
- Example producers in backup
- IO description in backup


## Base Stack

micromamba with conda-forge packages
$\rightarrow$ contains all required non-python packages, rarely updated (python3.9, bash/zsh, git, gfal2)
"cf" Sandbox
Relocatable python virtual env
$\rightarrow$ All python packages needed to run tasks,
moderately updated
(luigi, law, pyyaml)

## Task sandboxes

Any type: venv, cmssw subshell, docker, ...
$\rightarrow$ Python packages to run a specific task,

CMSSW
(subshell)
(e.g. awkward, numpy, tensorflow, ...)

# Example: muon weight producer (as shown earlier) 

```
@producer(
    uses={
    },"nMuon", "Muon.pt", "Muon.eta",
    },
    produces={
        "muon_weight", "muon_weight_up", "muon_weight_down",
    },
    # only allowed on mc
    mc_only=True,
def muon_weights(
    self: Producer,
    events: ak.Array,
    muon_mask: ak.Array | type(Ellipsis) = Ellipsis,
> ak.Array
    |" ...Creates muon weights using the correctionlib. ./
    # flat absolute eta and pt views
    abs_eta = flat_np_view(abs(events.Muon.eta[muon_mask]), axis=1)
    pt = flat_np_view(events.Muon.pt[muon_mask], axis=1)
    # loop over systematics
    for syst, postfix
        ("sf", ""),
        ("systup","_up"),
        ("systdown", "_down"),
    ]:
        sf_flat = self.muon_sf_corrector(self.year, abs_eta, pt, syst)
        # add the correct layout to it
        sf = layout_ak_array(sf_flat, events.Muon.pt[muon_mask])
        (sf, over atl muons per event
        weight = ak.prod(sf, axis=1, mask_identity=False)
        events = set_ak_column(events, f"muon_weight{postfix}", weight, value_type=np.float32)
    return events
```

@producer decorator will create a class muon_weights
Example: muon weight producer (as shown earlier)
uses declares columns that should be read
@producer(
@producer
\}, "nMuon", "Muon.pt", "Muon.eta",
produces=\{
"muon_weight", "muon_weight_up", "muon_weight_down",
f, only allowed on me
produces declares columns to be written
only allowed on mc
Additional flags enable during checks, e.g.
def muon_weights(
self: Producer,

- mc_only (bool), data_only (bool)
- nominal_only (bool), shifts_only (set[str])
muon_mask: ak.Array | type(Ellipsis) = Ellipsis,
$\rightarrow$ **kwargs,
-> ak.Array:
\# flat absolute eta and pt views
Wrapped function becomes the main callable of the class \&
abs_eta = flat_np_view(abs(events.Muon.eta [muon_mask]), axis=1) always should at least accept events and $* *$ kwargs
\# loop over systematics
for syst, postfix in
("sf", ""),
("systup", "_up"),
("systdown", "_down"),
Use set_ak_column to conveniently add new columns
sf_flat = self.muon_sf_corrector(self.year, abs_eta, pt, syst)
\# add the correct layout to it
sf = layout_ak_array(sf_flat, events.Muon.pt [muon_mask])
Return all events
\# create the product over all muons per event
weight = ak.prod(sf, axis=1, mask_identity=False)
(selectors: return also a SelectionResult)
@producer decorator will create a class muon_weights
Example: muon weight producer (as shown earlier)
uses declares columns that should be read
@producer(
@prose
\} , ~ " M u o n " , ~ " M u o n ~ . p t " , ~ " M u o n . e t a " , ~
produces=\{
"muon_weight", "muon_weight_up", "muon_weight_down",
\#, only allowed on mc
produces declares columns to be written

Additional flags enable during checks, e.g.
def muon_weights(
self: Producer,

- mc_only (boot), data_only (boot)
- nominal_only (boot), shifts_only (set[str])
muon_mask: ak.Array | type(Ellipsis) = Ellipsis,
$\rightarrow$ **kwargs,
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Wrapped function becomes the main callable of the class \&
abs_eta = flat_np_view(abs(events.Muon.eta [muon_mask]), axis =1)
pt = flat_np_view(events.Muon.pt [muon_mask], axis=1)
always should at least accept events and **kwargs
\# loop over systematics
for syst, postfix in [
for syst, postfix
("sf", ""),
("systup", "_up"),
("systdown", "_down"),
Use set_ak_column to conveniently add new columns
]:
sf_flat = self.muon_sf_corrector(self.year, abs_eta, pt, syst)
\# add the correct layout to it
sf = 'ayout_ak_array(sf_flat, events.Muon.pt [muon_mask])
Return all events
(selectors: return also a SelectionResult)

\# create the product over all muons per event
weight = ak.prod(sf, axis=1, mask_identity=False)
\# store it
events = set_ak_column(events, f"muon_weight\{postfix\}", weight, value_type np.float32)
events
Where does the muon_sf_corrector come from?
- From previous slide: "Wrapped function becomes the main callable of the class"
$\rightarrow$ Called for every chunk of events during processing
- But
- How to setup objects before the actual event processing?
- How to define a custom dependency? (i.e., task(s) on whose outputs the producer depends)

- From previous slide: "Wrapped function becomes the main callable of the class"
$\rightarrow$ Called for every chunk of events during processing
- But
- How to setup objects before the actual event processing?
- How to define a custom dependency? (i.e., task(s) on whose outputs the producer depends)


## - Three additional hooks

- init(self) -> None
- Method called as soon as producer registered by a task
$\triangleright$ Receives important task variables via self (requested dataset, shift, ...)
- requires(self, reqs: dict) -> None
- Method called when task declares its dependcies
$\triangleright$ Allows injecting custom dependencies into reqs that will be resolved by luigi
- setup(self, reqs: dict, inputs: dict, reader_targes: dict) -> None
- Method called in task's run() once before loop over event chunks
$\Delta$ Receives reqs defined before and corresponding inputs

$\triangleright$ Allows setting up objects to be used in main callable


## 16 Writing your own producer (calibrator, selector, ...) (3)

- init(self) -> None

```
@jer.init
aet Jer_Init(self: Calibrator) -> None:
    if self.propagate_met:
        self.uses |= {
        "MET.pt", "MET.phi",
    }
    self.produces |= {
        "MET.pt", "MET.phi", "MET.pt_jer_up", "MET.pt_jer_down", "MET.phi_jer_up",
        "MET.phi_jer_down", "MET.pt_unsmeared", "MET.phi_unsmeared",
    }
```

from calibration/cms/jets.py

- requires(self, reqs: dict) -> None


## @muon_weights.requires

det muon_weights_requlres(self: Producer, reqs: dict) $\rightarrow$ None: from columnflow.tasks.external import BundleExternalFiles reqs["external_files"] = BundleExternalFiles.req(self.task)
from production/cms/muon.py

- setup(self, reqs: dict, inputs: dict, reader_targes: dict) -> None


## @muon_weights.setup

aet muon_weignts_setup(self: Producer, reqs: dict, inputs: dict, reader_targets: InsertableDict) -> None: bundle = reqs["external_files"]

## \# create the corrector

correctionlib.highlevel.Correction._call__ = correctionlib.highlevel.Correction.evaluate correction_set = correctionlib. CorrectionSet. from_string(
self.get_muon_file(bundle.files).load(formatter="gzip"). decode("utf-8"),
)
corrector_name, self.year = self.get_muon_config()
self.muon_sf_corrector = correction_set[corrector_name]










```
> law run cf.PlotVariables1D\
    --version dev1 \
    --datasets hh_bbtautau
    --calibrators jec \
    --selector full \
    --producers all_weights \
    --variables jet1_pt \
    --shift tauid_up
```

- Handling of systematics
- fully outsourced to task dependency resolution
- efficient, no unnecessary computations
- executable with high parallelism

- Python framework for vectorized, columnar HEP analysis with nano-like inputs
- Mostly experiment agnostic core
- Fully orchestrated \& automated
- Intermediate outputs
- Efficient through on-demand column production \& retrieval
- Able to incorporate any remote resource

- Checks $15 / 17$ "ideal workflow"items of CMS ATTF report (Sec. 4, backup)
- Vast Python (HEP) community and tool landscape is key
- Currently pushing for extensive documentation release
- Feedback still highly appreciated !
- github.com/columnflow, columnflow.rtfd.io

columnflow technicalities


## - Case 1: Create histograms

■ law run cf.CreateHistograms --dataset tt \}
--producers my_features --variables jet*

- Loads default columns from "MergeReducedEvents" plus columns created by a producer called "my_features"

```
@producer(
    uses={"Jet.pt", "Jet.phi"},
    produces={"Jet.px", "Jet.py"},
def my_features(self: Producer, events: ak.Array, **kwargs) -> ak.Array:
    events = set_ak_column_f32(events, "Jet.px", events.Jet.pt * np.cos(events.Jet.phi))
    events = set_ak_column_f32(events, "Jet.py", events.Jet.pt * np.sin(events.Jet.phi))
    return events
```


## - Case 1: Create histograms

■ Law run cf.CreateHistograms --dataset tt \}
--producers my_features --variables jet*

- Loads default columns from "MergeReducedEvents" plus columns created by a producer called "my_features"

```
@producer(
    uses={"Jet.pt", "Jet.phi"},
    produces={"Jet.px", "Jet.py"},
def my_features(self: Producer, events: ak.Array, **kwargs) -> ak.Array:
    events = set_ak_column_f32(events, "Jet.px", events.Jet.pt * np.cos(events.Jet.phi))
    events = set_ak_column_f32(events, "Jet.py", events.Jet.pt *-np.sin(events.Jet.phi))
        events
```

- Case 2: Create different histograms

■ law run cf.CreateHistograms --dataset tt \}
--producers my_features,event_shapes --variables jet*

- Loads default columns from "MergeReducedEvents" plus columns created producers "my_features" and "event_shapes"

```
@producer(
    uses={"..."}
    produces={"..."},
)
def event_shapes(self: Producer, events: ak.Array, **kwargs) >> ak.Array:
    events = set_ak_column_f32(events, "fox_wolfram1", ...)
    events = set_ak_column_f32(events, "subjettiness", ....)
    `..'
        events
```

- Only processes "event_shapes", reuses columns from "my_features"



## Layering of columns

e.g. in SelectEvents

Updated columns (by CalibrateEvents)

Original columns (from NanoAOD)

Combined columns


- Each task handles a single input in one* process (* or more if needed)
- Single input = potentially multiple files with different columns for the same events
- Orchestration allows processing on any resource
- Highly parallel when running over all inputs
- Loop over event chunks in single thread, offload IO waits to thread pool


## lazy loading

main thread


- Each task handles a single input in one* process (* or more if needed)
- Single input = potentially multiple files with different columns for the same events
- Orchestration allows processing on any resource
- Highly parallel when running over all inputs
- Loop over event chunks in single thread, offload IO waits to thread pool


Straight-forward integration of dask_awkward
$\rightarrow$ Map chunks to partitions
$\rightarrow$ compute() partitions in thread-pool
$\rightarrow$ Single-node dask graph
$\rightarrow$ Provide result to main thread
$\square$ F1.1 Executable in "one go"
$\square$ F1.2 Output intermediate results on demand
$\square$ F1.3 Identify and rerun only necessary components
$\square$ F1.4 Composition of columns to easy reuse / sharing
$\square$ F1.5 Reproducibility via CI/CD
$\square$ F1.6 Version checkpointing
$\square$ F1.7 Support for custom NANO inputF2.1 Non-imperative paradigmF2.2 Physics object representation for NANO objects
$\square$ F2.3 Seamless handling of systematic uncertainties
$\square$ F2.4 Automatic datacard writing
$\boxminus$ F2.5 Analysis results in different formats (datacards, pyhf workspace, HEPData, ...)
$\square$ F2.6 Export to / import from dedicated, static workflow language
F2.7 Workflow configuration separated from analysis codeF2.8 Multidimensional histogramsF3.1 Resource agnosticismF3.2 Easily scalable (local, multi-core, batch)

> law \& luigi

- Portability: Does the analysis depend on ...
- where it runs?
- where it stores data?
$\triangleright$ Execution/storage should not dictate code design!
- Reproducibility: When a postdoc / PhD student leaves, ...
- can someone else run the analysis?
- is there a loss of information? Is a new framework required? ■ Dependencies often only exist in the physicists head!


## HICondur <br> High Throughput computing




- Preservation: After an analysis is published
- are people investing time to preserve their work?
- can it be repeated after O (years)?
$\triangleright$ Daily working environment should provide preservation features out-of-the-box!

- Personal experience: $2 / 3$ of "analysis" time for technicalities, $1 / 3$ left for physics
$\rightarrow$ Physics output doubled if it were the other way round?


- Most analyses are both large and complex
- Structure \& requirements between workloads mostly undocumented
- Manual execution \& steering of jobs, bookkeeping of data across SEs, data revisions, ...
$\rightarrow$ Error-prone \& time-consuming

- In the following
$\rightarrow$ Approach complexity with

$\rightarrow$ Enabling large-scale with
law


Tailored systems

- Structure "iterative", a-priori unknown
- Dynamic workflows, fast R\&D cycles
- DAG with arbitrary dependencies
- Incorporate any existing infrastructure
- Use custom software, everywhere

Wishlist for end-user analyses

- Structure known in advance
- Workflows static \& recurring
- One-dimensional design
- Special production infrastructure
- Homogeneous software requirements
$\rightarrow$ Requirements for HEP analyses mostly orthogonal
- Python package for building complex pipelines
github.com/spotify / luigi
- Development started at Spotify, now open-source and community-drive

| $\bigcirc$ Watch - | 493 | * Unstar | 15.2k | \&゚ Fork | 2.3k |
| :---: | :---: | :---: | :---: | :---: | :---: |



- Luigi's execution model is make-like

1. Create dependency tree for triggered task
2. Determine tasks to actually run:

- Walk through tree (top-down)
- For each path, stop if all output
- Only processes what is really necessary
- Scalable through simple structure
- Error handling \& automatic re-scheduling


[^0]```
# reco.py
import luigi
from my_analysis.tasks import Selection
class Reconstruction(luigi.Task):
    dataset = luigi.Parameter(default="ttH")
    def requires(self):
        return Selection(dataset=self.dataset)
    def output(self):
        return luigi.LocalTarget(f"reco_{self.dataset}.root")
    def run(self):
        inp = self.input() # output() of requirements
        outp = self.output()
        # perform reco on file described by "inp" and produce "outp"
        .,.
```

> python reco.py Reconstruction --dataset ttbar

```
# reco.py
import luigi
from my_analysis.tasks import Selection
```

Parameter object on class-level
class Reconstruction(luigi.Task):
string on instance-level
dataset $=$ luigi.Parameter(default="ttH")
def requires(self):
return Selection(dataset=self.dataset)
def output(self):
return luigi. LocalTarget(f"reco_\{self.dataset\}. root")
def run(self): $\quad$ Encoding parameters into
inp = self.input() \# output() of requirements
outp $=$ self.output()
\# perform reco on file described by "inp" and produce "outp"
.,


- law: extension on top of luigi (i.e. it does not replace luigi)
- Software design follows 3 primary goals:

1. Experiment-agnostic core (in fact, not even related to physics)
luigi analysis workflow
2. Scalability on HEP infrastructure (but not limited to it)
3. Decoupling of run locations, storage locations \& software environments

- Not constrained to specific resources
$\triangleright$ All components interchangeable
- Toolbox to follow an analysis design pattern
- No constraint on language or data structures
$\rightarrow$ Not a framework
- Most used workflow system for analyses in CMS
- $\mathrm{O}(20)$ analyses, $\mathrm{O}(60-80)$ people
- Central groups, e.g. HIG, TAU, BTV


## 1. Job submission

- Idea: submission built into tasks, no need to write extra code
luígi analysis workflow
- Currently supported job systems: HTCondor, LSF, gLite, ARC, Slurm, CMS-CRAB
- Mandatory features such as automatic resubmission, flexible task $\leftrightarrow$ job matching, job files fully configurable at submission time, internal job staging when queues are saturated, ...
- From the htcondor_at_cern example:

```
lxplus129:law_test > law run CreateChars --workflow htcondor
INFO: [pid 30564] Worker Worker(host=lxplus129.cern.ch, username=mrieger) running
    CreateChars(branch=-1, start_branch=0, end_branch=26, version=v1)
going to submit 26 htcondor job(s)
submitted 1/26 job(s)
submitted 26/26 job(s)
14:35:40: all: 26, pending: 26 (+26), running: 0 (+0), finished: 0 (+0), retry: 0 (+0), failed: 0 (+0)
14:37:10: all: 26, pending: 0 (+0),
14:37:40: all: 26, pending: 0 (+0),
14:38:10: all: 26, pending: 0 (+0), running: 0 +0), finished: 26 (+10), retry: 0 (+0), failed:0
INFO: [pid 30564] Worker Worker(host=lxplus129.cern.ch, username=mrieger) done!
lxplus129:law_test >



\section*{2. Remote targets}
- Idea: work with remote files as if they were local
luigi analysis workflow
- Remote targets built on top of GFAL2 Python bindings
\(\triangleright\) Supports all WLCG protocols (XRootD, WebDAV, GridFTP, dCache, SRM, ...) + DropBox
- API identical to local targets
! Actual remote interface interchangeable (GFAL2 is just a good default, fsspec integration easily possible)
- Mandatory features: automatic retries, local caching (backup), configurable protocols, round-robin, ...

\section*{"FileSystem" configuration}
```


# law.cfg

[wlcg_fs]
base: root://eosuser.cern.ch/eos/user/m/mrieger

```
- Base path prefixed to all paths using this "fs"
- Configurable per file operation (stat, listdir, ...)
- Protected against removal of parent directories
2. Remote targets
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Conveniently reading remote files
```


# read a remote json file

target = law.WLCGFileTarget("/file.json", fs="wlcg_fs")
with target.open("r") as f:
data = json.load(f)

```
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Conveniently reading remote files
```


# read a remote json file

target = law.WLCGFileTarget("/file.json", fs="wlcg_fs")

# use convenience methods for common operations

data = target.load(formatter="json")

```
2. Remote targets
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- Mandatory features: automatic retries, local caching (backup), configurable protocols, round-robin, ...

Conveniently reading remote files
```


# same for root files with context guard

target = law.WLCGFileTarget("/file.root", fs="wlcg_fs")
with target.load(formatter="root") as tfile:
tfile.ls()

```
2. Remote targets
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- API identical to local targets
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Conveniently reading remote files
```


# multiple other "formatters" available

target = law.WLCGFileTarget("/model.pb", fs="wlcg_fs")
graph = target.load(formatter="tensorflow")
session = tf.Session(graph=graph)

```

\section*{2. Remote targets}
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- API identical to local targets
! Actual remote interface interchangeable (GFAL2 is just a good default, fsspec integration easily possible)
- Mandatory features: automatic retries, local caching (backup), configurable protocols, round-robin, ...
```

def run(self):
\# get the input to this task, which is a *.gz file
\# (the output of the requirements)
inp = self.input()
\# create the correction set
import correctionlib
correction_set = correctionlib.CorrectionSet.from_string(
inp.load(formatter="gzip"),
)

```

3. Environment sandboxing
- Diverging software requirements between typical workloads
luigi analysis workflow is a great feature / challenge / problem
- Introduce sandboxing:
\(\triangleright\) Run entire task in different environment
- Existing sandbox implementations:
- Sub-shell with init file (e.g. for CMSSW)
- Virtual envs
\(\triangleright\) Docker images
\(\triangleright\) Singularity images

docker::imgA anteence

singularity::cc7

```


# reco.py

import luigi
from my_analysis.tasks import Selection
class Reconstruction(luigi.Task):
dataset = luigi.Parameter(default="ttH")
def requires(self):
return Selection(dataset=self.dataset)
def output(self):
return luigi.LocalTarget(f"reco_{self.dataset}.root")
def run(self):
inp = self.input() \# output() of requirements
outp = self.output()
\# perform reco on file described by "inp" and produce "outp"
:."

```
```


# reco.py

import luigi
import law
from my_analysis.tasks import Selection
class Reconstruction(law.Task):
dataset = luigi.Parameter(default="ttH")
def requires(self):
return Selection(dataset=self.dataset)
def output(self):
return law.LocalFileTarget(f"reco_{self.dataset}.root")
def run(self):
inp = self.input() \# output() of requirements
outp = self.output()
\# perform reco on file described by "inp" and produce "outp"

```
        -••
```


# reco.py

import luigi
import law
from my_analysis.tasks import Selection
class Reconstruction(law.Task, law.HTCondorWorkflow):
dataset = luigi.Parameter(default="ttH")
def requires(self):
return Selection(dataset=self.dataset)
def output(self):
return law.LocalFileTarget(f"reco_{self.dataset}.root")
def run(self):
inp = self.input() \# output() of requirements
outp = self.output()
\# perform reco on file described by "inp" and produce "outp"
\#:

```
> law run Reconstruction --dataset ttbar --workflow htcondor
```


# reco.py

import luigi
import law
from my_analysis.tasks import Selection
class Reconstruction(law.Task, law.HTCondorWorkflow):
dataset = luigi.Parameter(default="ttH")
def requires(self):
return Selection(dataset=self.dataset)
def output(self):
return law.WLCGFileTarget(f"reco_{self.dataset}.root")
def run(self):
inp = self.input() \# output() of requirements
outp = self.output()
\# perform reco on file described by "inp" and produce "outp"

```
        -••
> law run Reconstruction --dataset ttbar --workflow htcondor
```


# reco.py

import luigi
import law
from my_analysis.tasks import Selection
class Reconstruction(law.SandboxTask, law.HTCondorWorkflow):
dataset = luigi.Parameter(default="ttH")
sandbox = "docker::cern/cc7-base"
def requires(self):
return Selection(dataset=self.dataset)
def output(self):
return law.WLCGFileTarget(f"reco_{self.dataset}.root")
def run(self):
inp = self.input() \# output() of requirements
outp = self.output()
\# perform reco on file described by "inp" and produce "outp"
\#:"

```
> law run Reconstruction --dataset ttbar --workflow htcondor

\section*{- CLI}
> law run Reconstruction --dataset ttbar --workflow htcondor
- Full auto-completion of tasks and parameters

\section*{- Scripting}
- Mix task completeness checks, job execution \& input/output retrieval with custom scripts
- Easy interface to existing tasks for prototyping

\section*{- Notebooks}
```

from analysis.tasks import Selection
import akward as ak

# create the task and ensure it's complete

task = Selection(dataset="ttH_bb", version="v3", shift="nominal")
task.law_run() < _

# read the selected events (a . parquet file)

events = task.output().load(formatter="awkward")

# get the number of jets per event

n_jets = ak.num(events.Jet, axis=1)
print(n_jets)

```

In
```

[5]: %law run ShowFrequencies --print-status -1
print task status with max_depth -1 and target_depth 0
> ShowFrequencies(slow=False)
_1 > MergeCounts(slow=False)
LocalFileTarget(fs=local_fs, path=$DATA_PATH/chars_merged.json)
                existent
            > CountChars(file_index=1, slow=False)
                LocalFileTarget(fs=local_fs, path=$DATA_PATH/chars_1.json)
existent
-3 > FetchLoremIpsum(file_index=1, slow=False)
LocalFileTarget(fs=local_fs, path=\$DATA_PATH/loremipsum_1.txt)
existent

```
- Print character frequencies in the "loremipsum" placeholder text (from examples/loremipsum)
- Fetch 6 paragraphs as txt files from some server
\(\triangleright\) Count character frequencies and save them in json
\(\triangleright\) Merge into a single json file
\(\triangleright\) Print frequencies

- Sowing CLI usage in the following, but

Q launch binder
for the notebook version
order
- Pythonic class collection to help structuring CMS metadata
- Provides programmatic access to and relations between various entities
\begin{tabular}{lc} 
Name & \multicolumn{1}{c}{ Purpose } \\
\hline Analysis & Represents the central object of a physics analysis. \\
\hline Campaign & Provides data of a well-defined range of data-taking, detector alignment, MC settings, datasets, etc. \\
\hline Config & Holds analysis information related to a campaign instance (most configuration happens here!). \\
\hline Dataset & Definition of a dataset, produced for / measured in a campaign. \\
\hline Process & Phyiscs process with cross sections for multiple center-of-mass energies, labels, etc. \\
\hline Channel & Analysis channel, often defined by a particular decay resulting in distinct final state objects. \\
\hline Category & Category definition, (optionally) within the phase-space of an analysis channel. \\
\hline Variable & Generic variable description providing expression and selection statements, titles, binning, etc. \\
\hline Shift & Represents a systematic shift with a name, direction and type. \\
\hline
\end{tabular}

- Examples
```

In [3]: dataset_ttH.get_process("ttH").get_xsec(ecm=13)
Out[3]: 0.5071 -0.0465532 (scale)

```
```

In [12]: cfg.get_variable("jet1_px").get_full_title(root=True)
Out[12]: 'jet1_px;Leading jet p_{x} / GeV;Entries / 20.0 GeV'

```
- Heavily used throughout columnflow, common objects (datasets and cross-sections) centralized in \(\boldsymbol{Q}\) /uhh-cms/cmsdb
- Note: Moving code-base to CMS-wide project via CAT group, datasets \& cross-sections to be managed centrally```


[^0]:    * in this case, the task is considered complete

