RECAST

Lukas Heinrich

LHCb Computing Workshop

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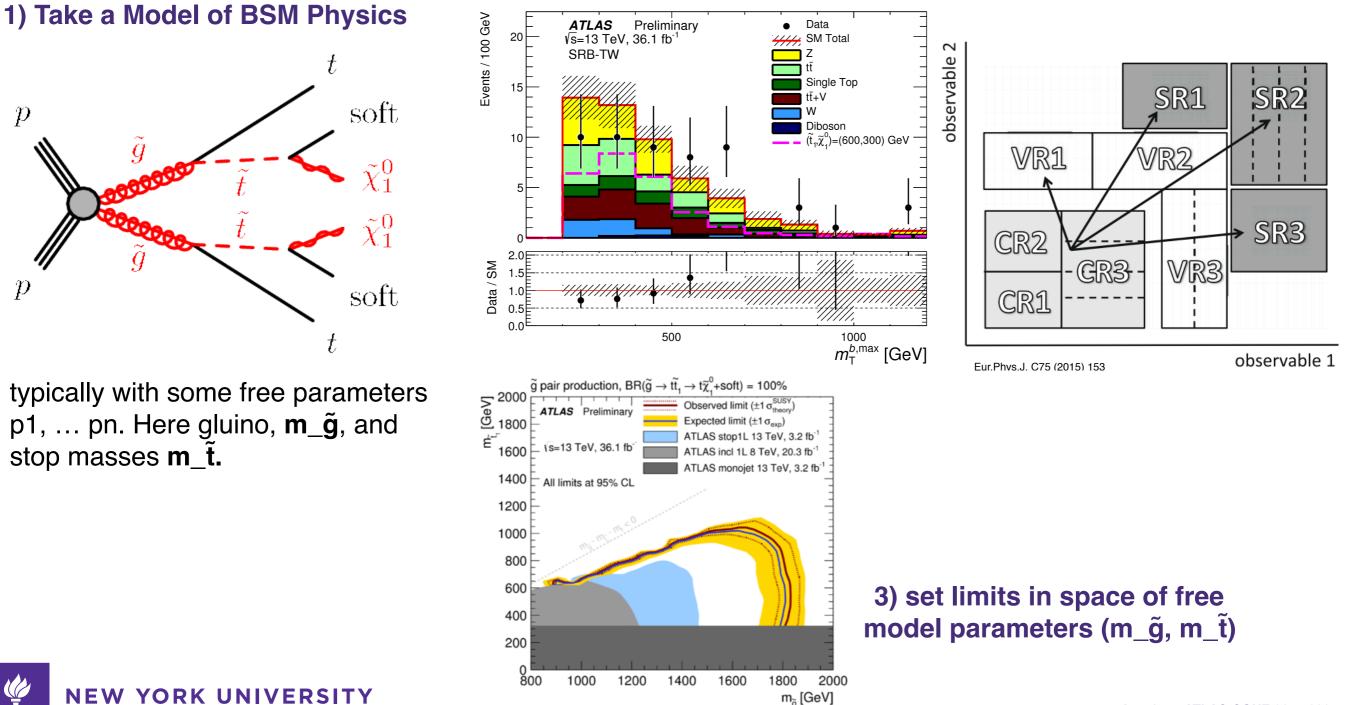
Searching for New Physics in ATLAS



Typical ATLAS Search for BSM Physics

2) Measure Data and estimate SM backgrounds

mix of data-driven and simulation-based (MC) background estimates. Signal from simulation.

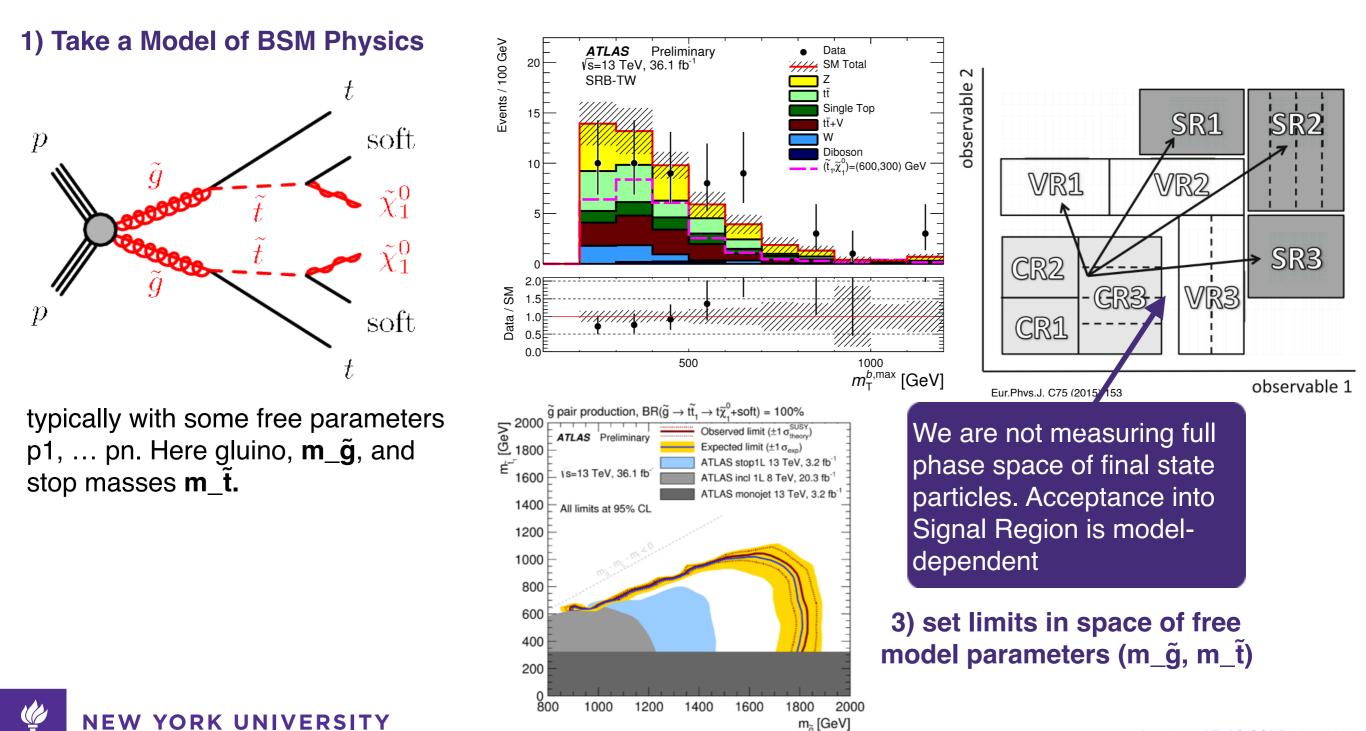


plots from ATLAS-CONF-2017-020

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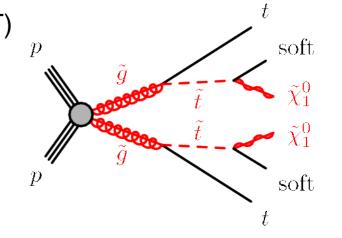
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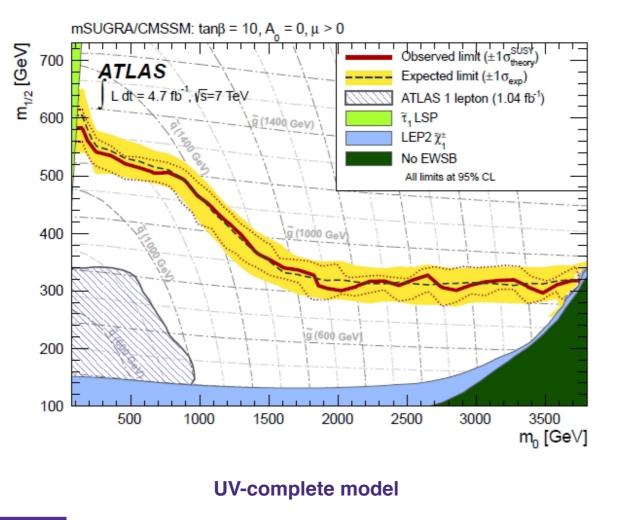


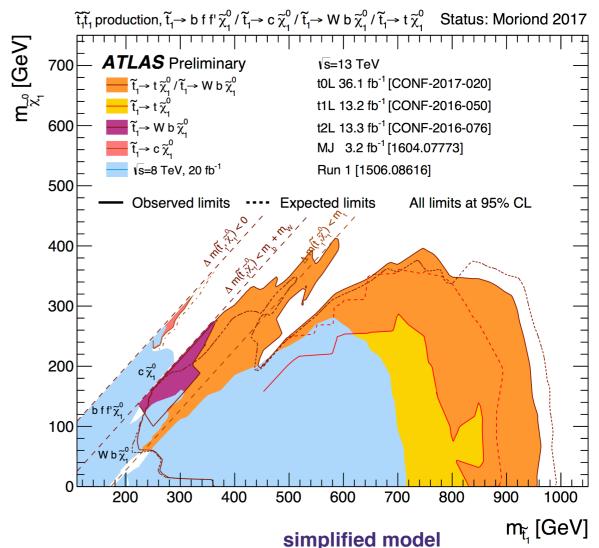
Typical ATLAS Search for BSM Physics

ATLAS has moved away from UV-complete models in favor of bottom-up 'simplified models':

- limited particle content focused on specific signature (e.g. tops + MET)
- reinterpretation for full model:
 - calculate BR into topology of simplified model
 - hard if not any one topology dominant. limits weaker for full theories than for simplified models









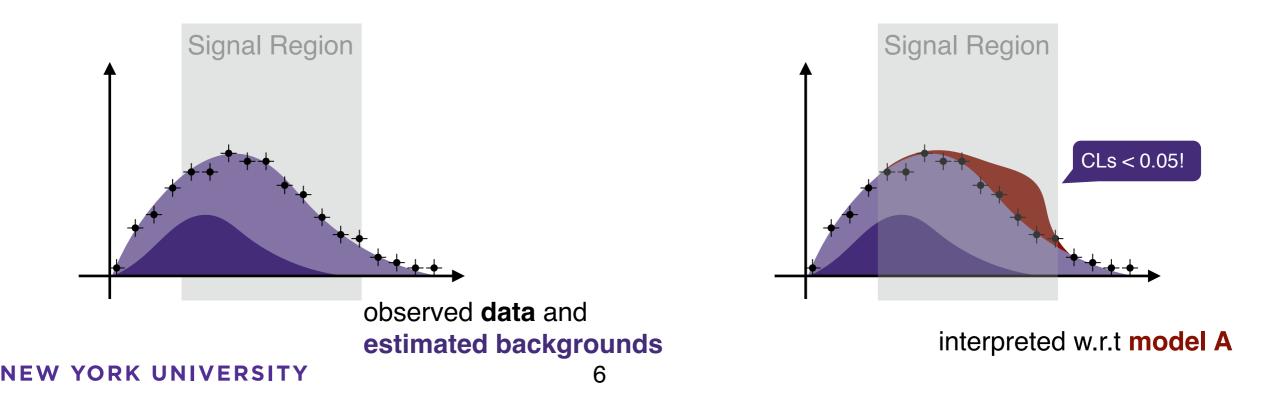
The analyses we prepare at the LHC are **high-effort**, **expensive projects**: non-trivial amount of personpower, time, and computing resources devoted to achieving a publication-quality result.

Most of the work goes into: **taking data, designing**, **validating** the analysis strategy, **understanding Standard Model backgrounds.** Effectively: a measurement of observed and backgrounds in interesting phase space regions.

Model interpretation come at the end, and are technically the **easiest part:** analysis pipeline is **fixed** after unblinding, MC dataset sizes small. Analysis teams routinely check hundreds of parameter points (of their favorite model).

But: most analyses only interpreted once within limited set of models.

- analysis team pushing for conference deadline
- interesting models proposed by hep-ph after they've seen the paper / note.



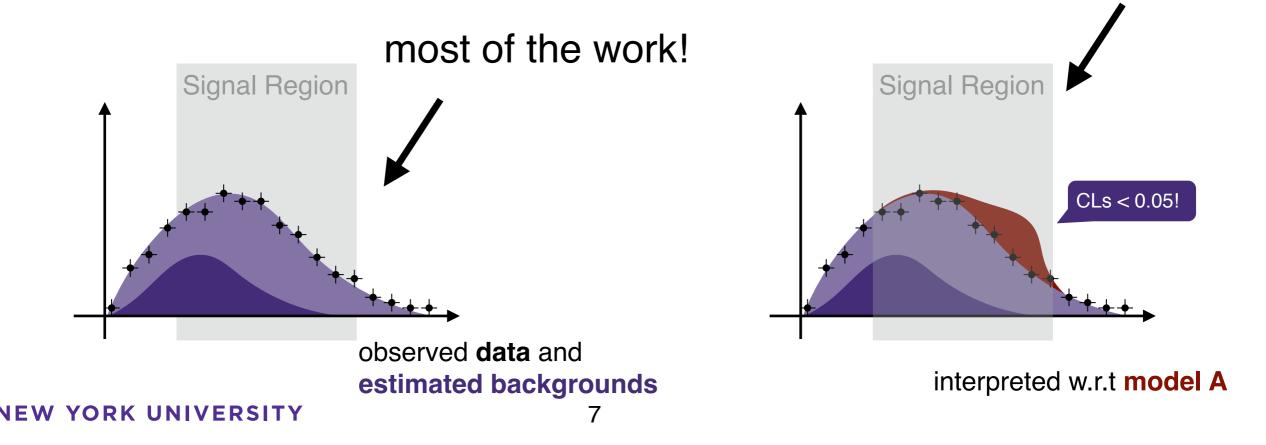
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~ easy

how to maximize scientific output of an analysis?

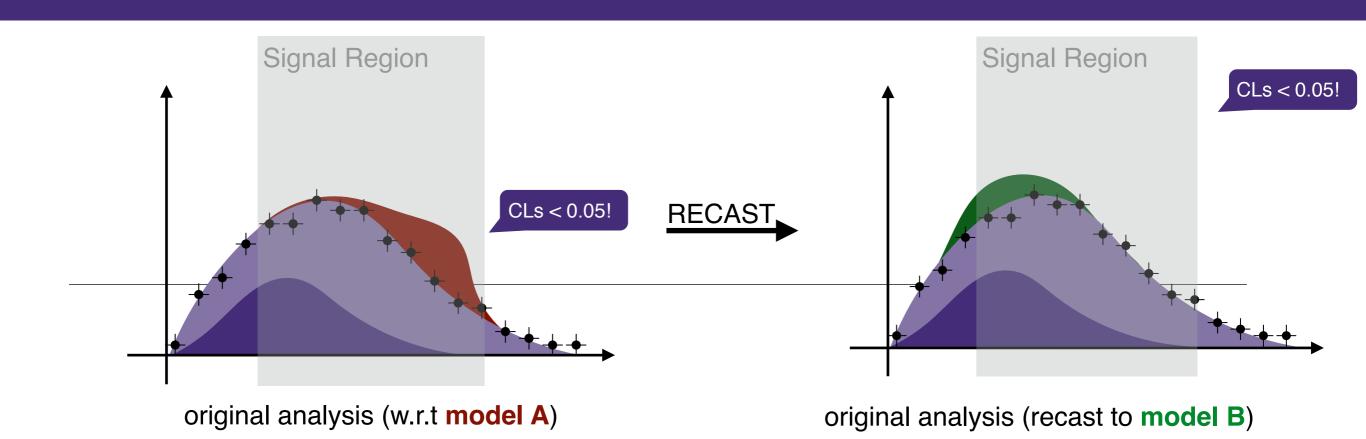


how to maximize scientific output of an analysis?

make analyses (rapidly) reusable.

reinterpret analyses w.r.t multiple models after publication





Reinterpretation Recipe:

At publication time:

- 1. archive data + background estimates in fully reduced form, i.e. as histograms / unbinned ntuples
- preserve original analysis pipeline (at least such that we can run new signal sample). Not necessary to preserve ability to re-derive background estimates

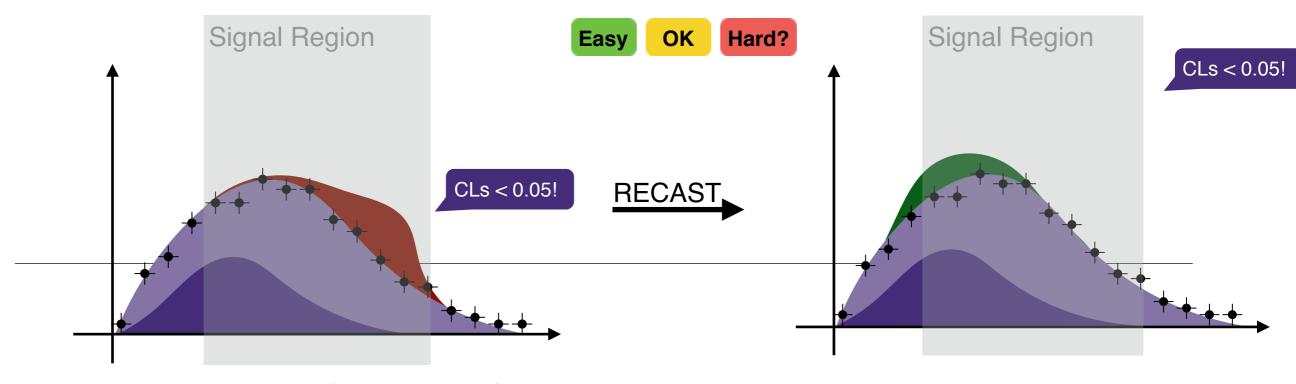
Later:

1. Generate **new signal dataset** with same/compatible settings as original analysis (simulation, reconstruction, etc...)

after sanity checks, e.g. DM abundance, cross-section, H mass, approx. SR acceptance)

2. Run dataset through **original analysis pipeline**, compare/fit against archived data and backgrounds.

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original analysis (w.r.t model A)

original analysis (recast to **model B**)

Reinterpretation Recipe:

At publication time:

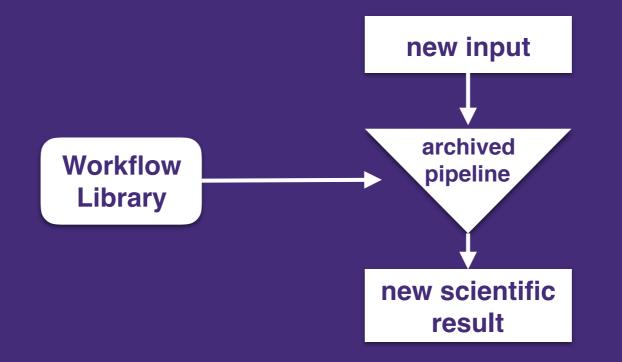
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need a way to capture analysis pipelines such that they can be re-executed on *new input*

Reusability not Reproducibility





Complexity:

capturing an analysis for RECAST is easier and harder than reproducing the original result

Easier:

- do not need to reproduce all aspects of analysis. certain parts of analysis are fixed
 - discriminant training, cut optimization
 - background estimation techniques
 - reconstruction algorithms
 - ...
- can save certain aspects of invariant data
 - observed data and background distributions in final reduced form (histograms)
 - no need for preservation of large background Monte Carlo datasets

Harder:

- need to be prepared for "arbitrary" input data
 - remove unnecessary hard-coded knowledge of model under consideration
- need to preserve process, not just audit/trace of what software was run on what data
 - need to know how to construct new jobs on new inputs based on e.g. templates

Analysis Preservation: two-step process

Modern HEP analysis:

• Multiple steps/code-bases, possibly developed by independent teams, with differing software requirements. Example: one team developing the event selection, another team developing the statistical analysis

Need to capture:

1. Individual processing steps

- code bases
- software environments
- identify binaries, scripts in code base
- templates how to run binaries (semantic description of arguments, naming etc..)
- · description of step output, what are the relevant data fragments

2. How to connect these steps

- How to wire individual steps together
- What outputs of which steps, are used as inputs for other steps, ...

Analysis Preservation:

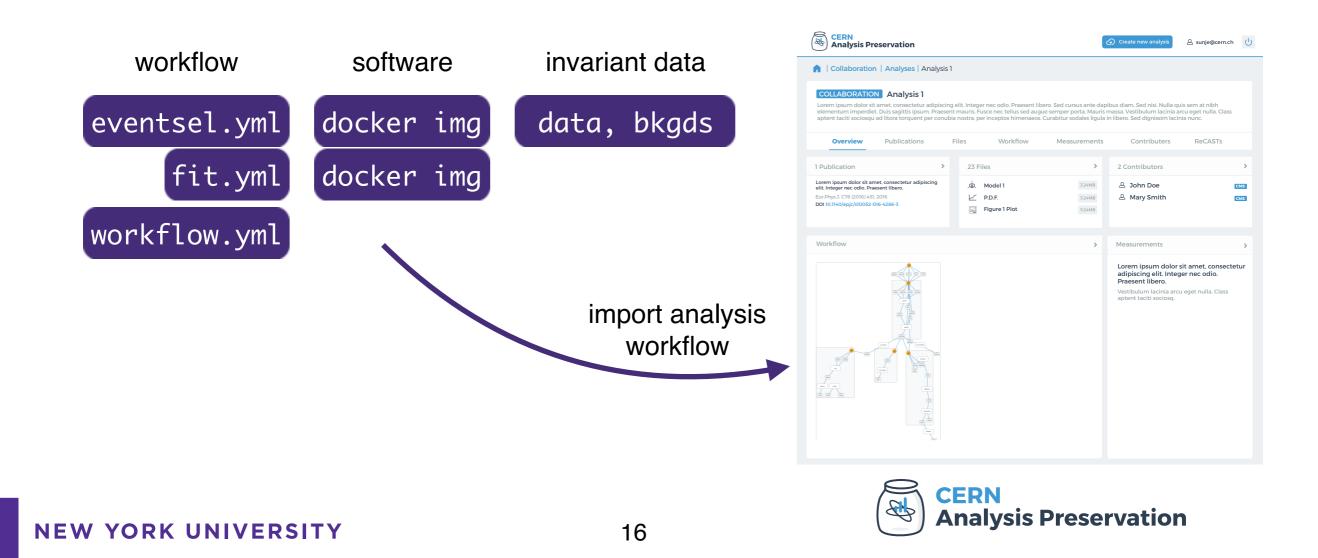
Some Goals

- composable: be able to re-use parts of pipeline from others, without changing yours
- run on generic compute: don't tie workflow description to specific technology, preserve relevant info, not how or where to run (no ganga / grid submission scripts please). assumption: Given some CPU, storage, memory, re-run you workflow
- machine-readable and -writable: make it easy to script e.g. compositions etc.
- invariant: capture moving parts once, do not depend on outside state
- easy: re-use well-known formats, technologies, make it easy to write for analysis teams
- **unintrusive:** adapt to you, not the other way around.
- fast: capturing an analysis should not take more than a few days. capture while developing

Analysis Workflow Preservation via yadage — rough outline

- Individual processing steps (packtivity): docker images to capture software, job templates as YAML files
- 2. Workflow (yadage): YAML file of recipe how to build graph of packtivities

Since it's all JSON based, it's easily shared, imported, processed by machines. Fully integrated into CERN Analysis Preservation



Examples: packtivities

three pieces:

parametrized process:

template job from which we can produce concrete job

template: "./DelphesHepMC <input file> <output file>"

concrete: "./DelphesHepMC /input/file/path.hepmc /output/file.root"

environment:

description of computing env in which above job can run. Best: docker image

publisher:

recipe how to extract JSON result data after job completion

e.g. globbing files in a work directory, just declaring some of the input parameters as outputs

process:	
<pre>process_type: 'string-interpolated-cmd'</pre>	
<pre>cmd: './steermadgraph.py proc.dat default_run.dat {</pre>	<pre>paramcard} {outputlhe} -e {events}'</pre>
publisher:	
<pre>publisher_type: 'frompar-pub'</pre>	
outputmap:	process:
lhefile: outputlhe	<pre>process_type: 'interpolated-script-cmd'</pre>
environment:	script:
environment_type: 'docker-encapsulated'	<pre>#!/bin/bash python cnosts prodConf py Bup I/input stop2 ison (outputdin) prodConf Bools py (inputfile)</pre>
<pre>image: lukasheinrich/recast_phenoexample</pre>	<pre>python create_prodConf.py Run-I/input_step2.json {outputdir} prodConf_Boole.py {inputfile} export USER=`whoami`</pre>
	source /cvmfs/lhcb.cern.ch/lib/LbLogin.shno-userarea
	lb-runuse AppConfig.v3r266use ProdConf Boole v30r1 gaudirun.py prodConf_Boole.py
	publisher:
	<pre>publisher_type: 'fromglob-pub'</pre>
	globexpression: '*.digi'
	outputkey: digifile
	environment:
	<pre>environment_type: 'docker-encapsulated'</pre>
NEW YORK UNIVERSITY	<pre>image: lukasheinrich/lhcbdev-derived</pre>
	resources:
	- CVMFS

yadage workflows: dynamic topologies built at run-time

Natural Data Model: directed acyclic graphs (DAGs)

- nodes: individual steps
- edges: dependency relations

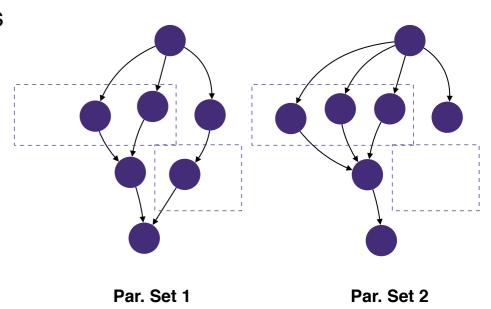
step 1 step 2 step 3 step 4 step 5 step 6

Two place where parametrization enter:

- 1. individual steps parametrized: covered by "packtivities"
- 2. graph topology may *depend on the parameters* of the analysis and only emerge during run-time

Examples:

- variable number of created files during execution,
- conditional choices (if/else)/flags do enable/disable steps, e.g. run systematics / not



yadage workflows: dynamic topolgies built at run-time

Therefore: Sequentially build up graph, as sufficient information becomes available, using a number of stages that add nodes and edges

To capture analysis workflow, capture the stages.

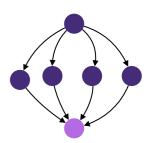
Example: Parametrized Map-Reduce

Stage 1: unknown number of files. e.g. download & unpack archive with a priori unknown # of files

Stage 2: for each file in the archive, add node to process it (only possible after first node done)

Stage 3:

add a node that merges results of the map nodes node/edge can be added before execution of map nodes



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step 6

step 3

step 5

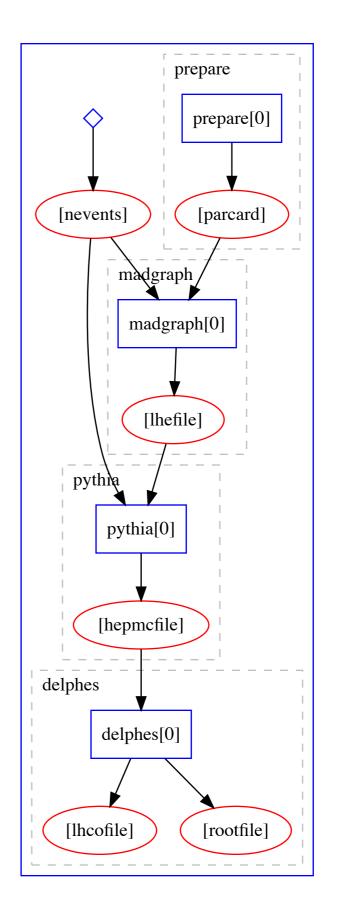
step 1

step 2

step 4

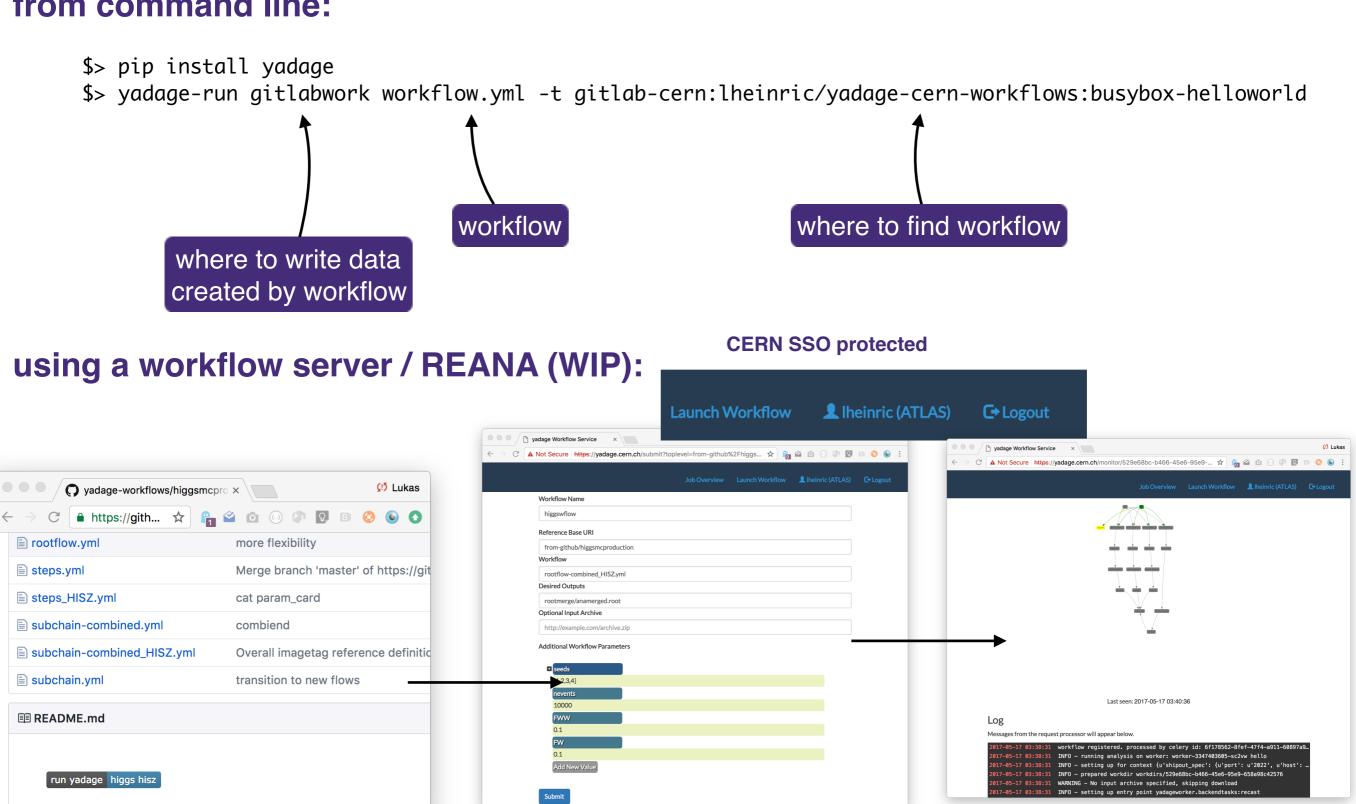
Examples: yadage workflows

three pieces: stages: - name: prepare dependencies: [] scheduler: scheduler_type: 'singlestep-stage' parameters: model: sm parametercard: '{workdir}/param.dat' inputpars: defaultparam.yml step: {\$ref: 'preparestep.yml'} - name: madgraph dependencies: ['prepare','init'] scheduler: scheduler_type: 'singlestep-stage' parameters: outputlhe: '{workdir}/output.lhe' events: {stages: init, output: nevents, unwrap: true} paramcard: {stages: prepare, output: parcard, unwrap: true} step: {\$ref: 'madgraph.yml'} - name: pythia dependencies: ['madgraph'] scheduler: scheduler_type: 'singlestep-stage' parameters: outputhepmc: '{workdir}/output.hepmc' events: {stages: init, output: nevents, unwrap: true} lhefile: {stages: madgraph, output: lhefile, unwrap: true} step: {\$ref: 'pythia.yml'} - name: delphes dependencies: - pythia scheduler: scheduler_type: 'singlestep-stage' step: {\$ref: 'delphes.yml'} parameters: outputroot: '{workdir}/output.root' outputlhco: '{workdir}/output.lhco' delphes_card: 'delphes/cards/delphes_card_ATLAS.tcl' inputhepmc: {stages: pythia, output: hepmcfile}



Executing yadage workflows

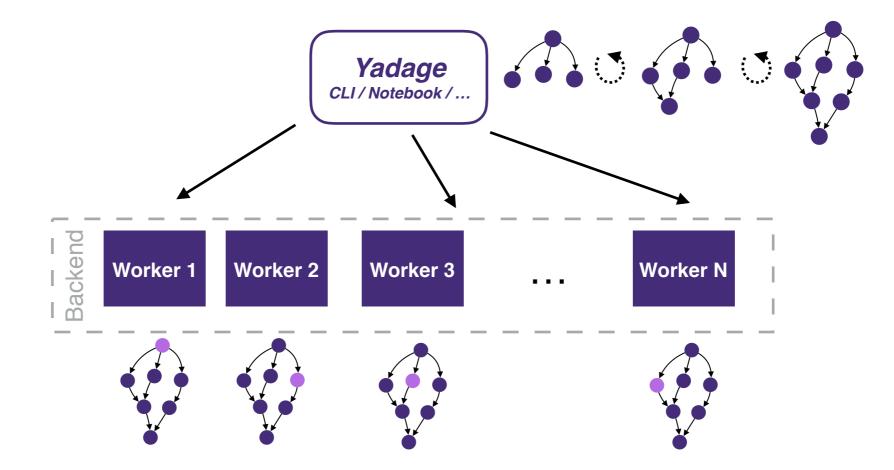
from command line:



Distributing Workflows across multiple Hosts in a workflow server

multiple backends possible: ipython clusters, kubernetes, celery. Backend should be able to run containers, as they are most common runtime spec.

On REANA, we re-use native Kubernetes Job API to distribute Jobs across cluster. Shared Storage via CephFS, experiement / archived data via EOS/ XrootD, Authentication via Kerberos / VOMS proxy.



LHCb experience

captured both production-type and analysis workloads in yadage

1. Monte Carlo Simulation/Reconstruction workflow: Gauss → Boole → MooreL0 → Moore → Brunel → DaVinci

2. Analysis:

Analysis separately developed in LHCb captured via Docker Container + internal workflow tool snakelike (simple workflow for yadage)

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Towards a streamlined RECAST service



RECAST Infrastructure Overview:

With archived analysis workflows it becomes feasible to streamline the reinterpretation efforts.

Reinterpretations as a collaboration- (or community-) wide service.

Originally suggested by Cranmer, Yavin [arXiv:1010.2506]



Idea:

- Produce reinterpretations of same fidelity as original result (not just approximations)
- Allow hep-ph community to suggest reinterpretations through a standard (web) interface. They
 provide most interesting points / scans to do. Auxiliary information such as run cards, SLHA
 spectra, UFO models
- LHC collaborations review suggestions and choose which to fulfill (based on scale of request, availability of a preserved analysis, physics case)
- Use archived analysis to (semi-) automatically run reinterpretation. Review results, approve (possibly on accelerated track, since analysis already approved).
- Publish and/or append original analysis HEPDATA record.
- Allows us to decouple original publication from reinterpretations. Publish early using benchmark signals, continuously re-interpret as samples become available

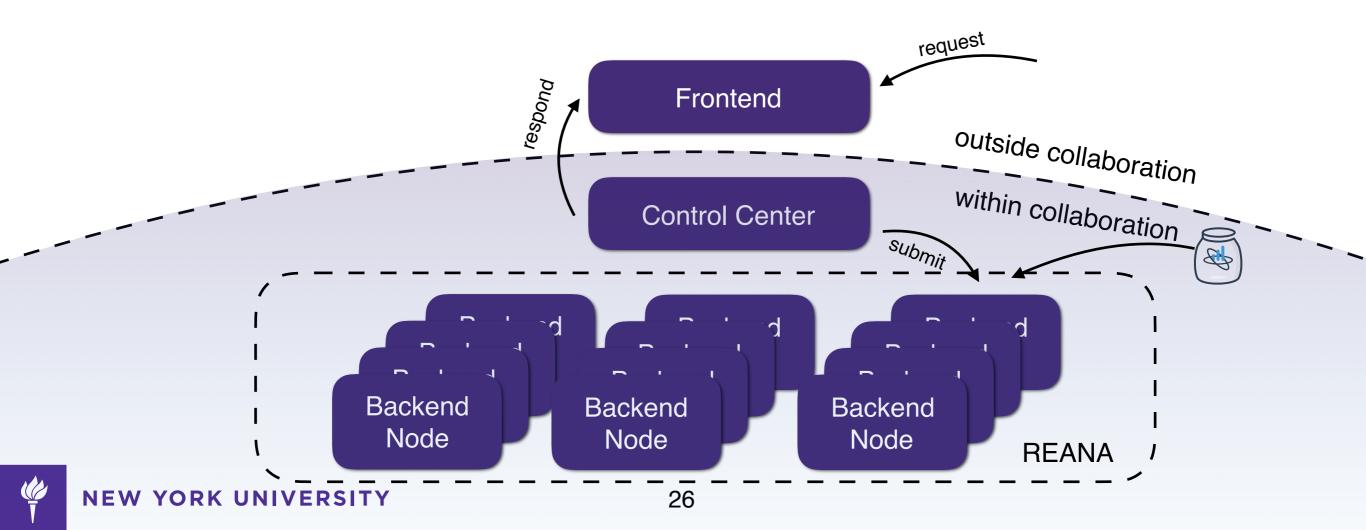
REANA: HEP workflows as a service

generic service offered at CERN, agnostic to type of workflow being run, semantics of why workflows are run

Based on REANA infrastructure / capability, we can enable physics applications / web services



RECAST: reinterpretations as a service

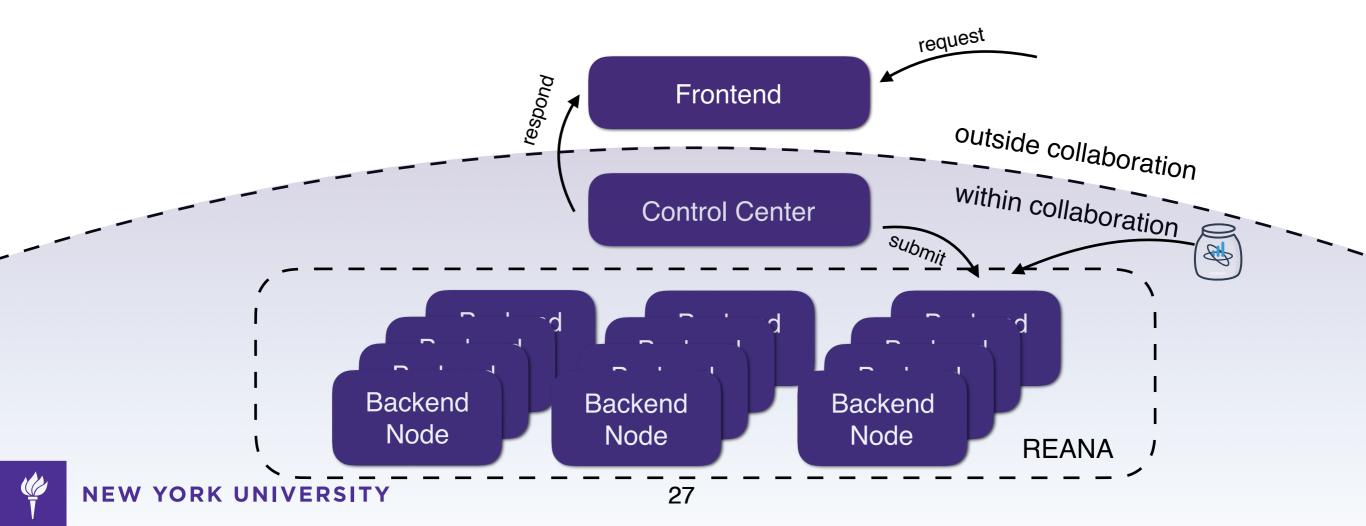


RECAST Overview:

Idea: Structured Interface between theory and experimental communities to assess BSM models

Theorists: propose models / parameter scans w.r.t. which to reinterpret a given analysis **Experimentalists:** asses proposals, if worthwhile;

- 1. Generate new Signal
- 2. Run archived analysis pipeline on new signal
- 3. review / approve results
- 4. publish results / append original paper





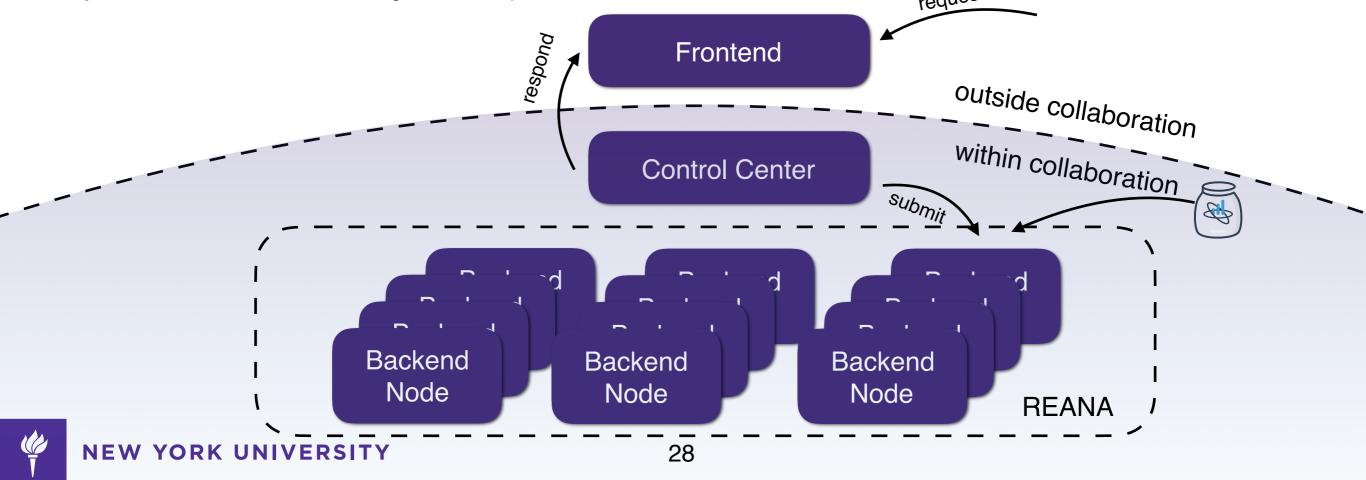
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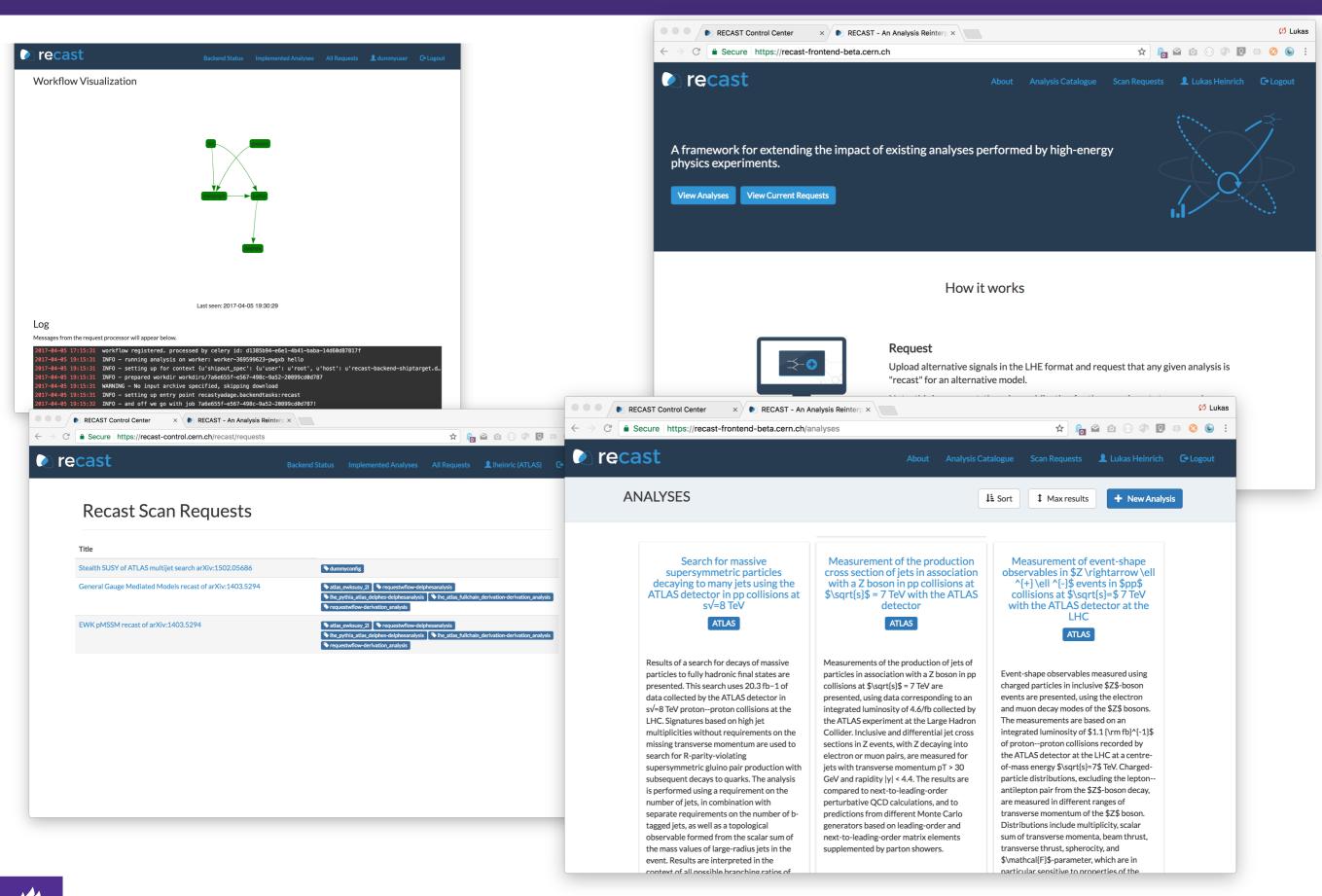
With archived analysis workflows it becomes feasible to streamline reinterpretations-as-a-service.

Frontend: public-facing web-service (+ API). Let's e.g. phenomenologists register interest in reinterpretations for specific published analyses. Allows them to provide auxiliary data (SLHA spectrum files, generator run cards, etc..). **Note:** No guarantee of fulfillment of request by collaborations.

Control Center: collaboration-internal web-service (+ API) to inspect incoming requests, compare against catalogue of archived analysis, allows submission to backend to actually perform reinterpretation. Can push "RECAST response" back to frontend.

Backend Cluster: distributed compute resource running on CERN OpenStack infrastructure to execute analysis workflows in order to get reinterpreted result

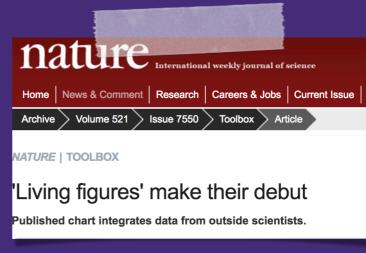




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Points of discussion for LHCb:

1. do you have use-case for parametrized pipelines? Adding data to a measurement? "Living Figure"?



2. do you have use-case for structured scientific interface between theory/experiment which would benefit from computational workflow backend? PHASE network?

Analysis preservation is not only for reproducibility.

Also new science result by re-using algorithms of analysis on new inputs. (reinterpretation)

yadage / packtivity: backend-agnostic workflow description in YAML. Integrated into CAP and RECAST projects. Distributed Workflows based on Containers.

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Recent Successes in Reusability...



It's the difference between if you had airplanes where you threw away an airplane after every flight, versus you could reuse them multiple times.

– Elon Musk

LHC analysis

It's the difference between if you/had airplanes where you threw away an airplane after every flight, versus you could reuse them multiple times.

checking one model

LHC analyses

– Elon Musk

Mar 30, 2017



Questions?

Appendix

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Case Study: Multi B-jets analysis

Defining the individual Workflow steps

- need script that tell us how to run the code once we are in the right environment. parametrized by a few variables (input file names etc)
- can use simple shell script, but also anything else

lumi/xsec/KF/FE weighting of HF tree

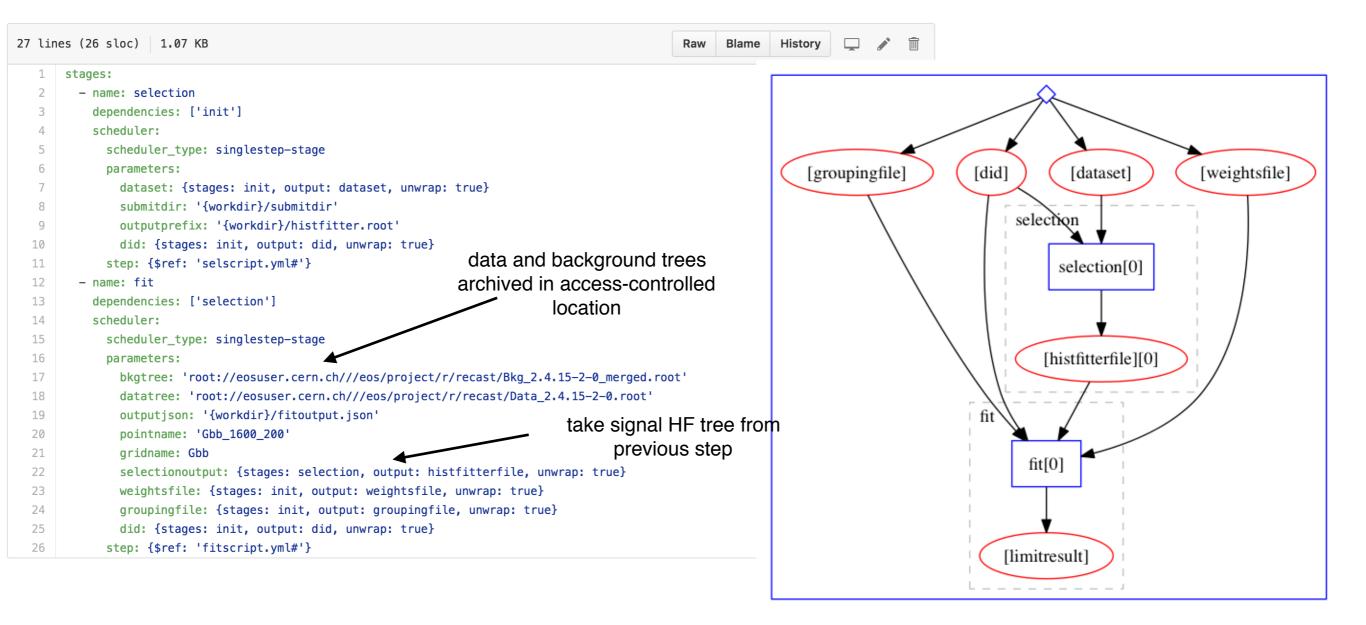
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22 Lines (22 slot) //4 Bytes Rev Blane History 1 process: 2 process: 3 script: 4 #/Jui/Jash 5 ecto "Hello" 5 source -/r.bashrc 5 setupATLAS 5 source -/r.Cestup.sh 9 /recast_auth/getmyproxy.sh 10 Listup fax dq2 11 python MultibletsAnalysis/scripts/Run.pydataSource 1doSyst 1doNTUP 0doxAOD 0do 12 mv (subhitdir)/data-output_histfitter/+.root (outputprefix).{did}.root 13 publisher: 14 publisher:type: 'fromglob-pub' 15 globespression: '*.root' 16 outputkey: histfitter/le 17 environment: 18 environment:type: 'docker-encapsulated' 19 jinge: Lukasheinrich/multibsel_cvmfs 20 resources: 21 - CWFS 22 - GRIDProxy direct SH Driver reads signal dataset (a SUSY10 derivation) 15 via XrootD writes out HistFitter tree	1 process: 2 process_type: 'interpolated-script-cmd' 3 script: 4 #!/bin/bash 5 source ~/.bashrc 6 setupATLAS 7 lsetup "root 6.06.02-x86_64-slc6-gcc48-opt" 8 cd /code/multib/HistFitter 9 source ./setup.sh 10 cd analysis_multib
	Run HF
NEW YORK UNIVERSITY	act Results into JSON format

Case Study: Multi B-jets analysis

Stringing the workflow together

- small file on how the individual pieces fit together.
- Here: dataset, AMI info file etc provided as input parameters, define EOS location of signal and background trees, declare that signal histfitter tree comes from previous selection step etc



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