Fair Universe: Unbiased Data Benchmark Ecosystem for Physics

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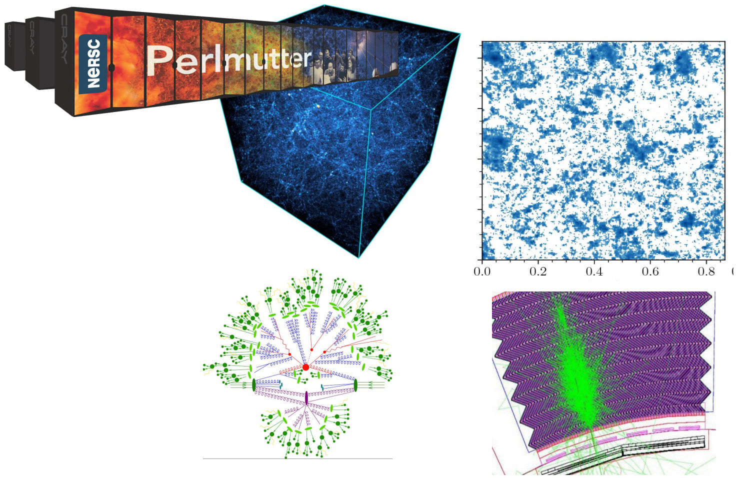
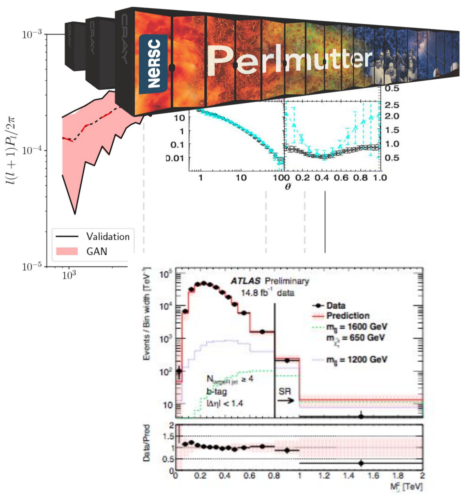
Background on Fair Universe Project

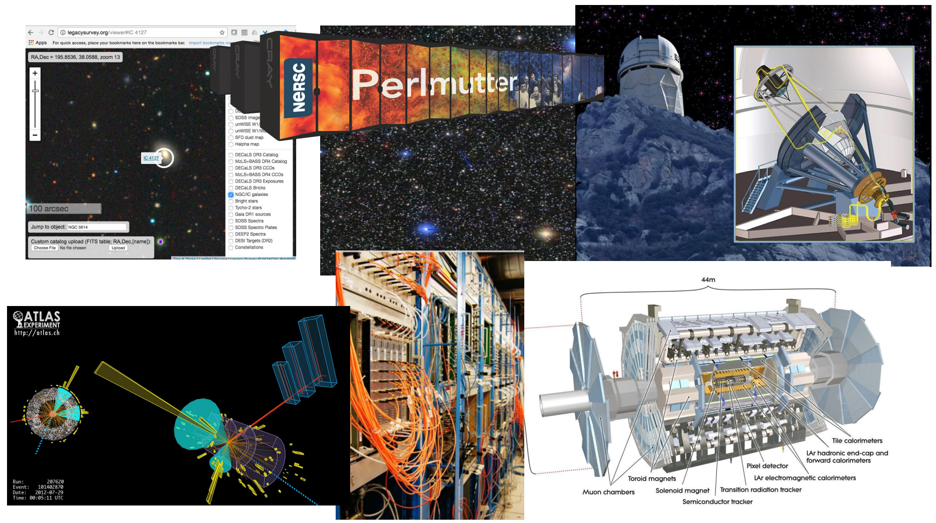
- 3 year US Dept. of Energy, AI for HEP project. Aims to:
  - Provide an open, **large-compute-scale AI ecosystem** for sharing datasets, training large models, fine-tuning those models, and **hosting challenges and benchmarks.**
  - **Organize a challenge series**, progressively rolling in tasks of increasing difficulty, based on novel datasets.
  - Tasks will focus on **measuring and minimizing the effects of systematic uncertainties** in HEP (particle physics and cosmology).
- Broad team in HEP, ML and computing involved in several previous challenges and benchmarks for HEP (e.g. HiggsML and TrackML) and wider (e.g NeurIPS competition track, MLPerf HPC); as well as Uncertainty aware learning in HEP

Measuring and minimizing the effects of systematic uncertainties in HEP

Bias and uncertainty in the fundamental sciences







Theory into Simulations

- High-resolution with detailed physics and instrument/ detector simulation

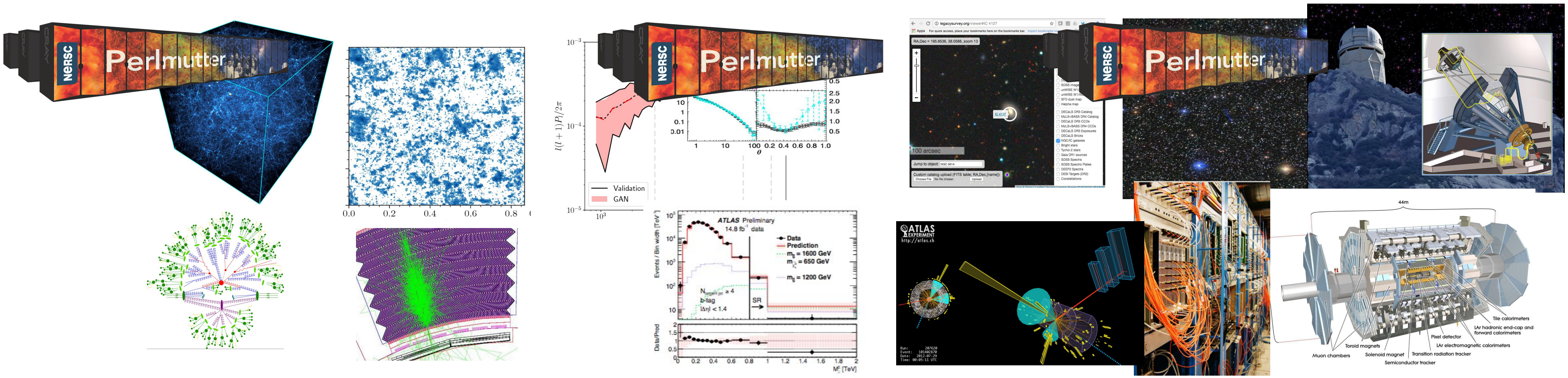
Summary statistics:

- E.g. 2pt /3pt correlation: spatial distribution
- E.g. Masses of reconstructed particles

Exp/Obs reconstruction

- Derive position of galaxies/stars and properties for catalogs
- Reconstruct particle properties

Bias and uncertainty in the fundamental sciences



Theory into Simulations

- Estimate Systematic Uncertainties (Z)

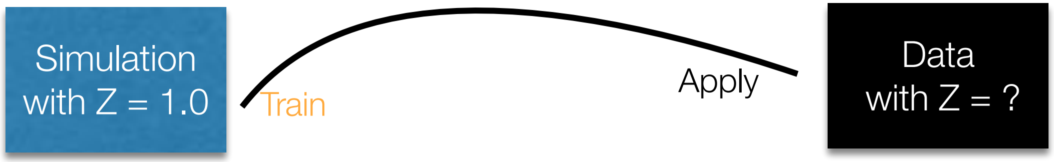
Exp/Obs reconstruction

- Detector state Z=?

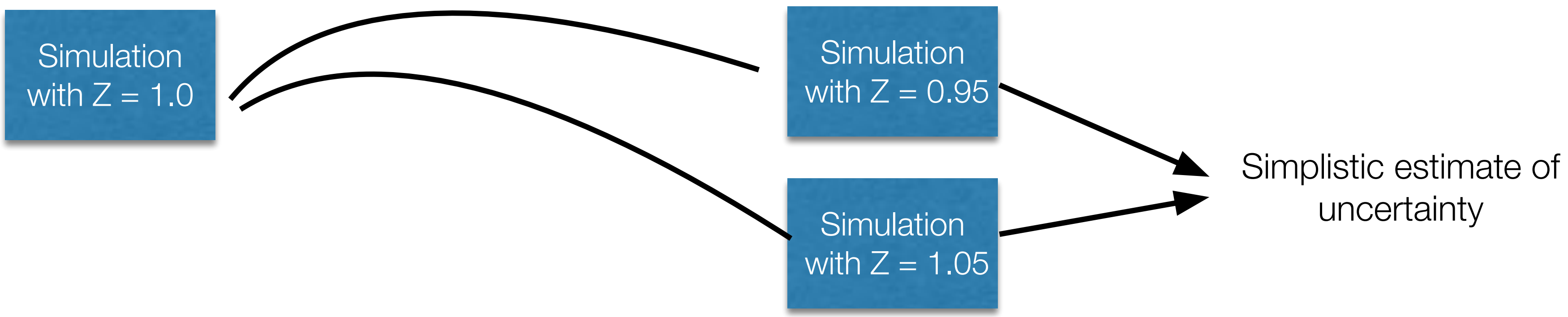
Differences between simulation and data can bias measurements

Bias and uncertainty in ML in the fundamental sciences

- ML methods in HEP are often trained based on simulation which has estimated systematic uncertainties (“Z”)
- These are then applied in data with the different detector state Z=?

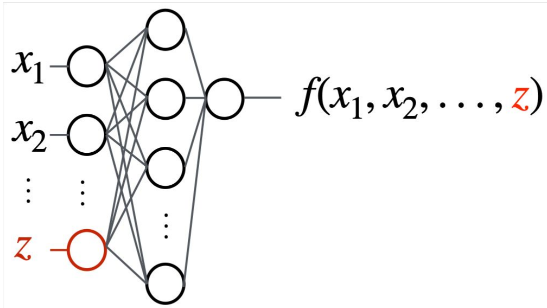


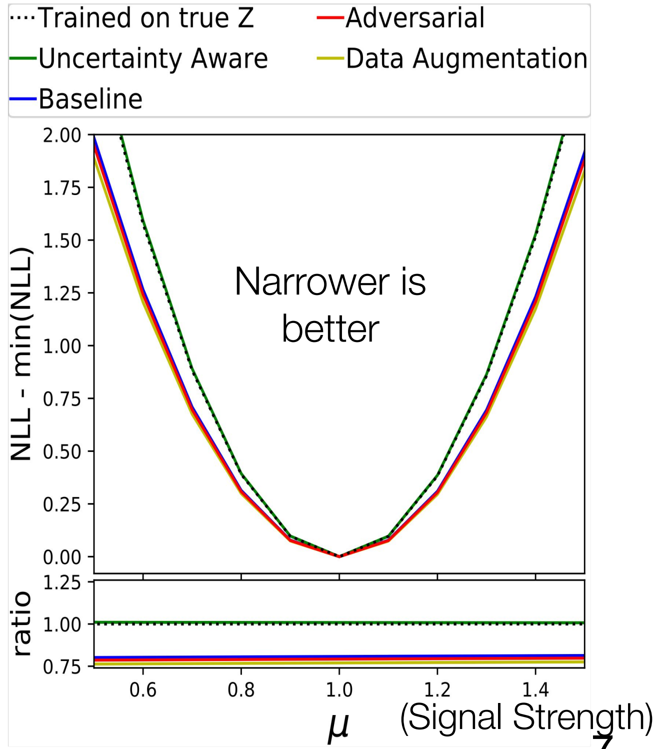
- Common baseline approach: Train classifier on nominal data (e.g. Z=1) and estimate uncertainties with alternate simulations. Shift Z and look at impact or perform full profile likelihood



Increasingly sophisticated approaches

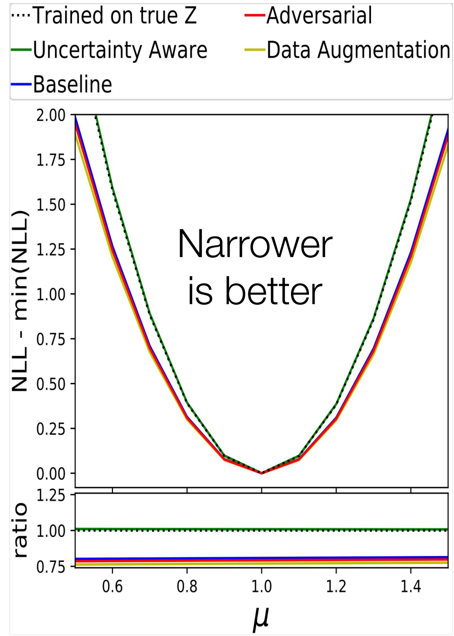
- Several focussed on decorrelation, e.g. augmentation; adversarial training; tangent propagation etc.
- “pivot” Louppe, Kagan, Cranmer : arXiv:1611.01046
- “Uncertainty-aware” approach of Ghosh, Nachman, Whiteson PhysRevD.104.056026
  - Parameterize classifier using Z
  - Measured on “Toy” 2D Gaussian Dataset and dataset from *HiggsML Challenge* modified to include systematic on tau-energy scale
  - Performs as well as classifier trained on true Z
- Other novel approaches e.g. (not comprehensive)
  - Inferno: arxiv:1806.04743
  - Direct profile-likelihood: e.g. arxiv:2203.13079

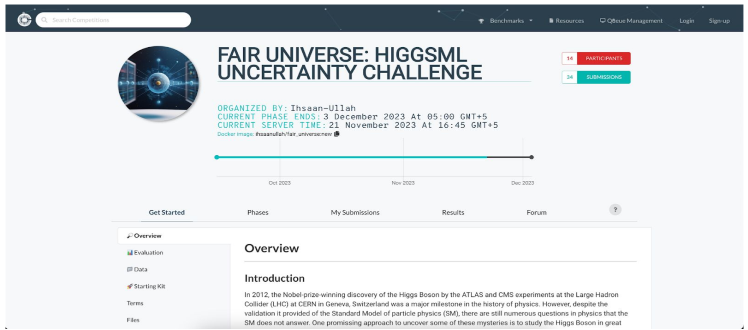




Progress requires new datasets, metrics, and platform

- Uncertainty-aware papers demonstrated on single systematic uncertainty, with limited data
- Original HiggsML dataset too small for ambitious approaches (systematic uncertainty small compared to statistical uncertainty)
- How to scale methods to many values of Z? (training difficulty increases, profiling approach used is expensive)
- Can faster methods allow for directly evaluating profile likelihood?
- Need for novel metrics to evaluate uncertainty determination for such methods

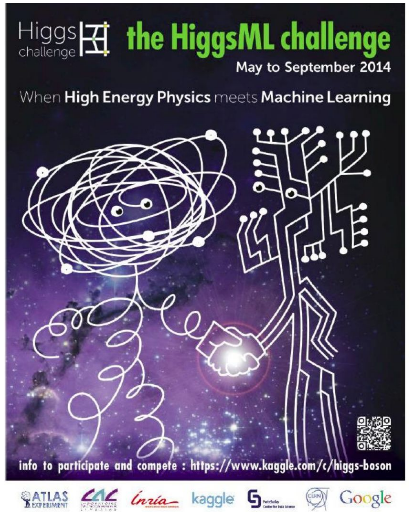




Organize a challenge series, progressively rolling in tasks of increasing difficulty, based on novel datasets

Fair Universe: HiggsML Uncertainty Challenge

- Extension of previous HiggsML challenge from 2014 (a classification problem for Higgs decaying to Tau leptons based on final state 3-momenta and derived quantities): l,h,MissingET,up to 2 jets
- Dataset : HiggsML 2014 data set on CERN Open Data portal doi:10.7483/OPENDATA.ATLAS.ZBP2.M5T8
- ⇒new Fair Universe dataset, with following improvements
- Instead of ATLAS G4 simulation, use Pythia LO + Delphes
- Numbers of events 800.000⇒ >10 millions
- Parametrised systematics (Nuisance Parameters) :
  - Tau Energy Scale : on had Tau Pt (and correlated MET)
  - Jet Energy Scale (and correlated MET impact)
  - additional randomised Soft MEt
  - background normalisation
  - W background normalisation (a subdominant poorly constrained BKG)
- Task : given a pseudo-experiment with given signal strength, provide a Confidence Interval



Pseudo-experiments

Test Dataset

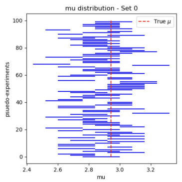
{x, w}

Create pseudo experiments for each test cases

{**x**, **w**$_1$}, w_1 = Pois (w)

Case 1

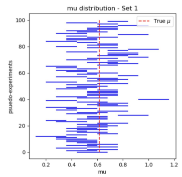
{NP}={NP}$_1$ $\mu = \mu_1$



{**x**, **w**$_2$}, , w_2 = Pois (w)

Case 2

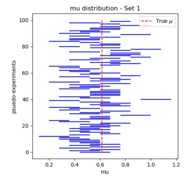
{NP}={NP}$_2$ $\mu = \mu_2$



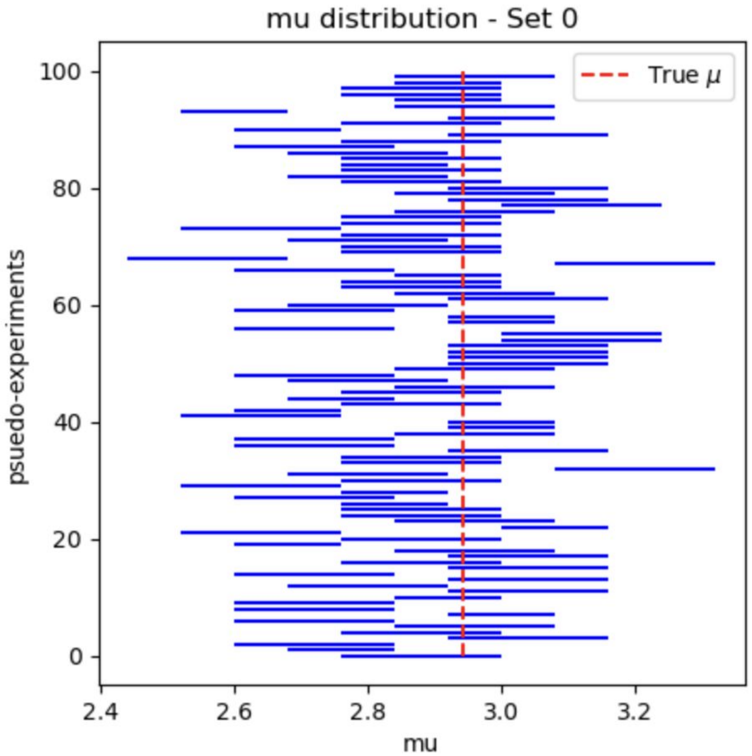
{**x**, **w**$_N$}, , w_N = Pois (w)

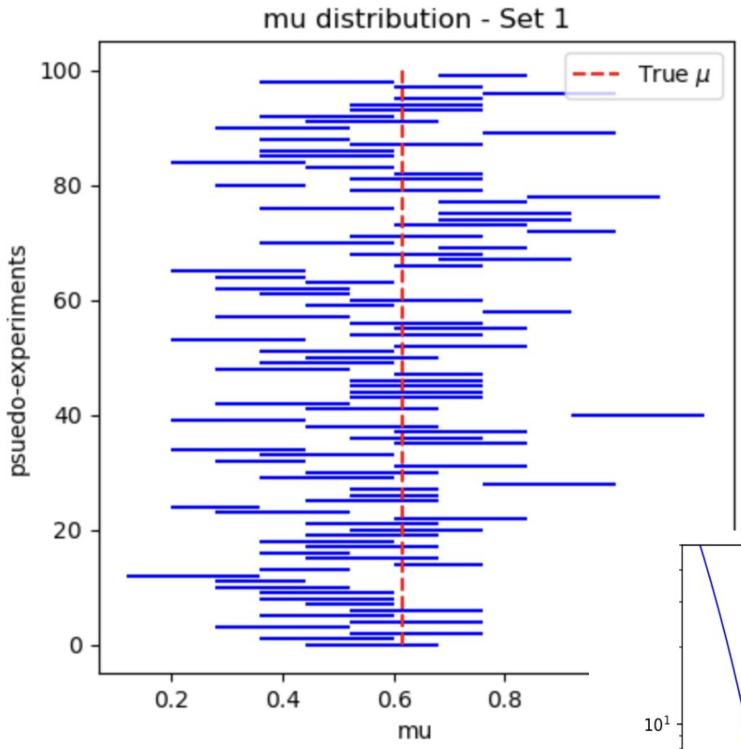
Case N

{NP}={NP}$_N$ $\mu = \mu_N$

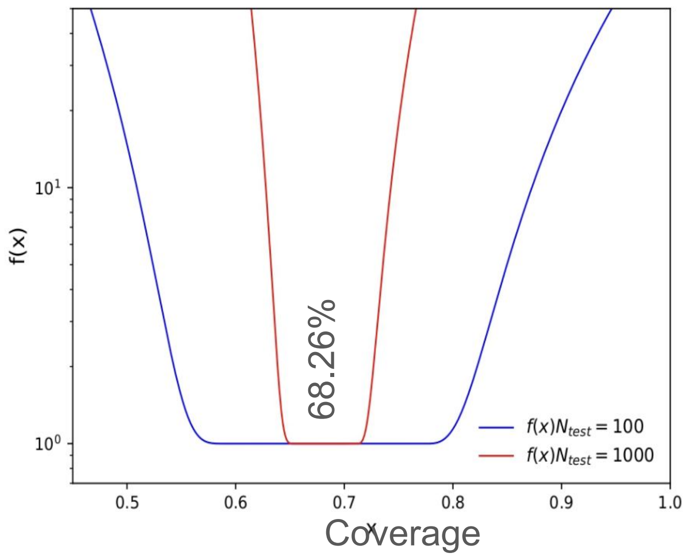


Coverage evaluation





Coverage penalisation function



score : <CI length> x coverage penalisation

sd

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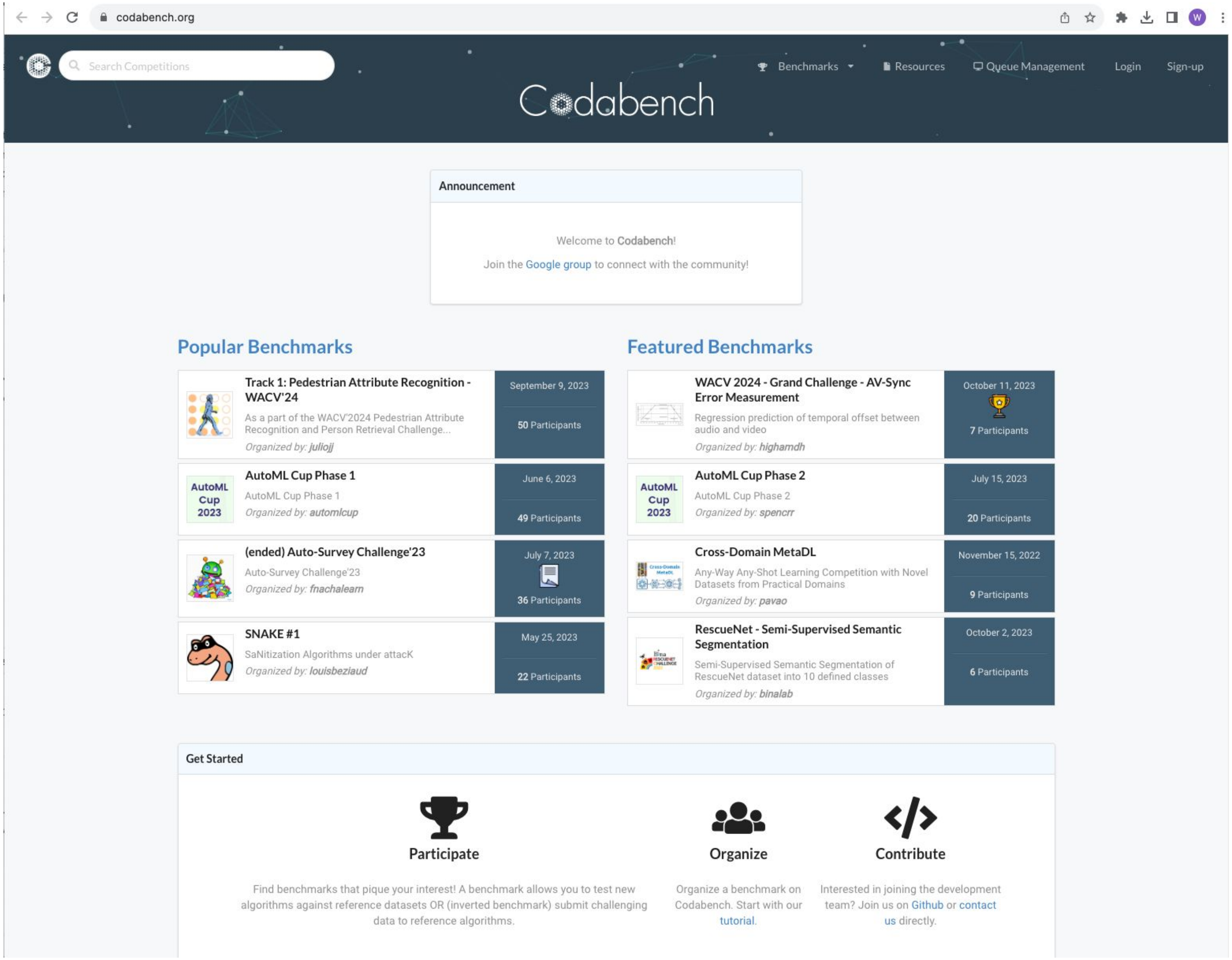
Task:				Fact Sheet Answers	Higgs Uncertainty Challenge			
#	Participant	Entries	Date of last entry	Method Name	Quantile Score	Interval	Coverage	Detailed Results
1	ragansu	30	2024-01-22	Histogram_10	**1.45**	0.226	0.57	
2	ragansu	30	2024-01-22	One_bin NLL	**1.07**	0.333	0.57	
3	laurensslu	20	2023-12-01	cheat7	**0.68**	0.504	0.63	
4	laurensslu	20	2023-12-01	cheat7	**0.61**	0.544	0.68	
5	laurensslu	20	2023-12-01	cheat4	**0.31**	0.732	0.61	
6	laurensslu	20	2023-12-01	cheat4	**0.16**	0.852	0.71	
7	laurensslu	20	2023-12-01	Cheat2	**-0.44**	1.55	0.62	
8	laurensslu	20	2023-12-01	Cheat2	**-0.74**	1.375	0.55	
9	ragansu	30	2024-01-22	tes_finder	**-0.95**	1.124	0.54	
10	laurensslu	20	2023-12-01	Cheat2	**-1.59**	1.325	0.53	
11	Ihsan Ullah	4	2024-01-18	Sascha sys aware 8	**-2.69**	0.329	0.47	
12	Rafał Masełek	10	2023-12-01	1binNLL	**-2.9**	1.233	0.5	
13	ihsanchalearn	16	2023-12-18	1 bin NLL	**-2.9**	1.233	0.5	
14	Rafał Masełek	10	2023-12-01	1binNLL	**-2.9**	1.233	0.5	
15	ihsanchalearn	16	2023-12-18	Sascha sys aware 8	**-3.01**	0.33	0.46	

Large-compute-scale AI ecosystem … hosting challenges and benchmarks.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As a part of the WACV'2024 Pedestrian Attribute Recognition and Person Retrieval Challenge...
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50 Participants
AutoML Cup Phase 1
AutoML Cup Phase 1
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49 Participants
(ended) Auto-Survey Challenge'23
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20 Participants
Cross-Domain MetaDL
Any-Way Any-Shot Learning Competition with Novel Datasets from Practical Domains
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RescueNet - Semi-Supervised Semantic Segmentation
Semi-Supervised Semantic Segmentation of RescueNet dataset into 10 defined classes
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Get Started
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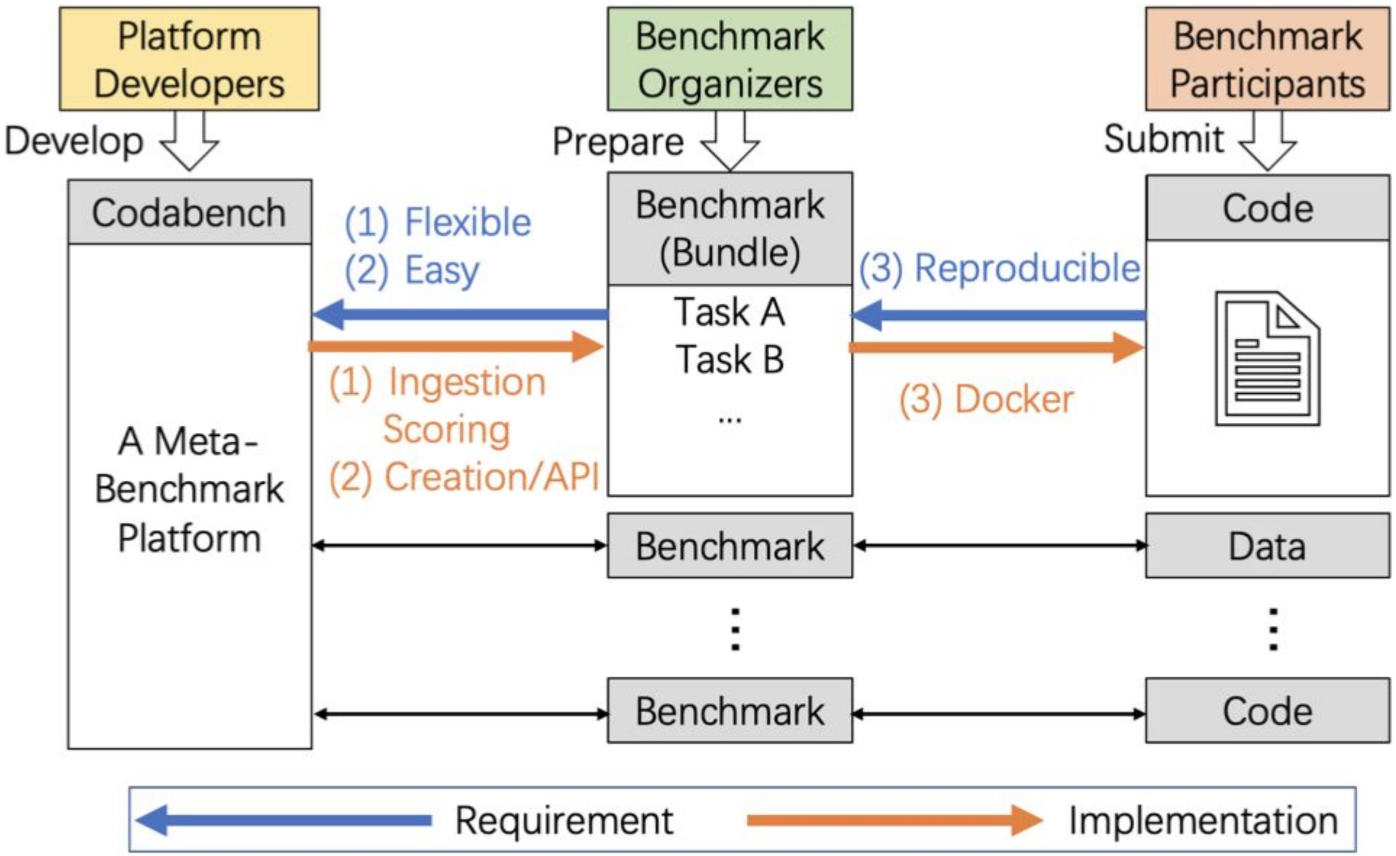
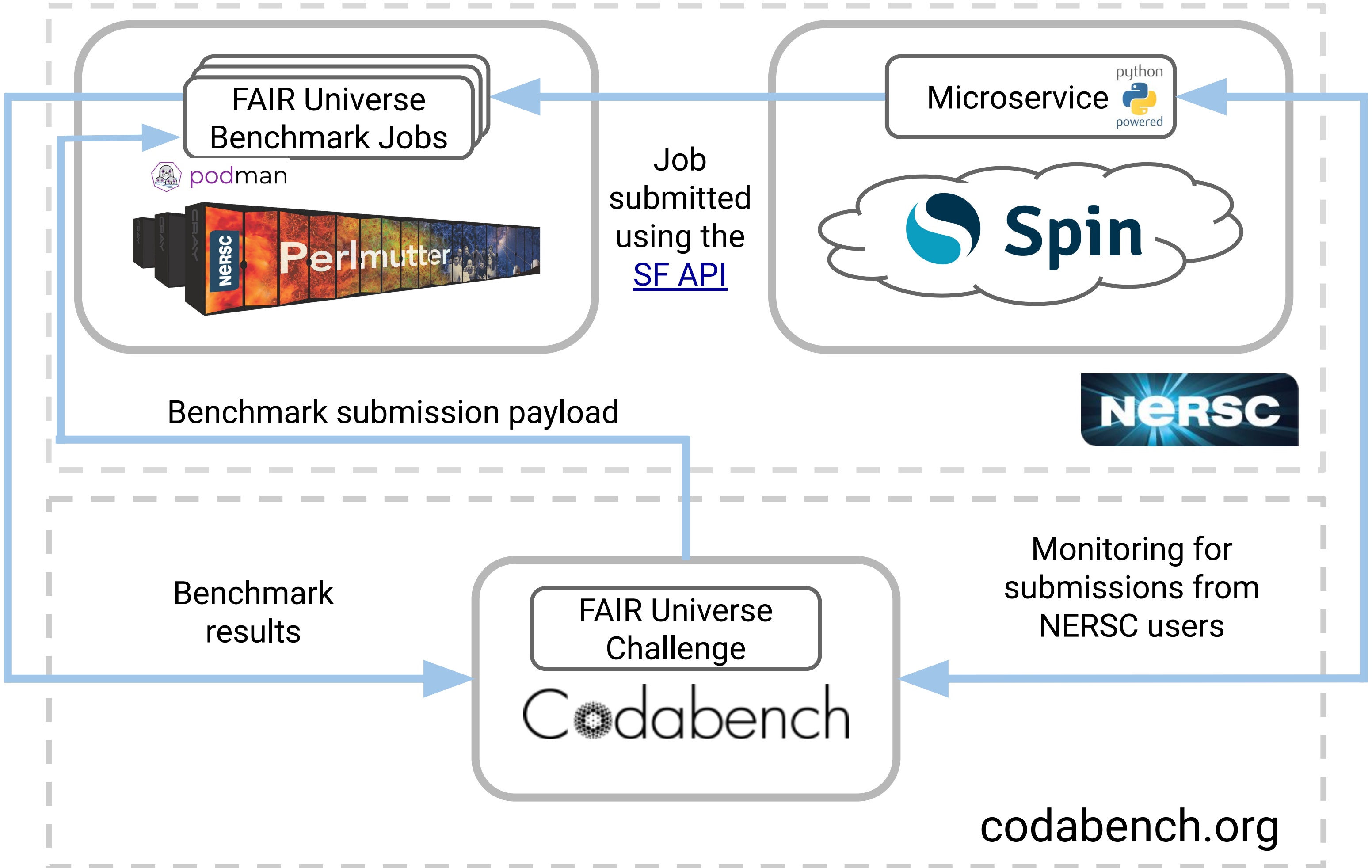
Find benchmarks that pique your interest! A benchmark allows you to test new algorithms against reference datasets OR (inverted benchmark) submit challenging data to reference algorithms.
Organize
Organize a benchmark on Codabench. Start with our tutorial.
Contribute
Interested in joining the development team? Join us on Github or contact us directly.

Codabench/“Fair Universe” Platform

Based on https://www.codabench.org/



Fair Universe Platform: Current Codabench/NERSC integration



Conclusion

- a major new scientific competition on measuring Higgs cross-section,
  - taking into account/minimizing impact from modelisation systematics
  - winner to provide a narrow confidence interval with good coverage
- on Codabench platform with NERSC back-end for precise evaluation of submissions
- early prototype run as part of Paris AI uncertainties workshop in Nov 2023
- to run June-Sep 2024
- we're applying for being a NeurIPS 2024 competition
- Will be announced on : lhc-machinelearning-wg@cern.ch

- A cosmology challenge (weak-lensing) is also in the pipeline