pyhf: auto-differentiable binned HEP likelihoods

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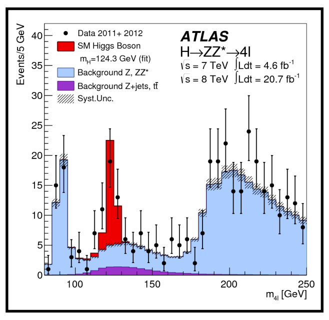
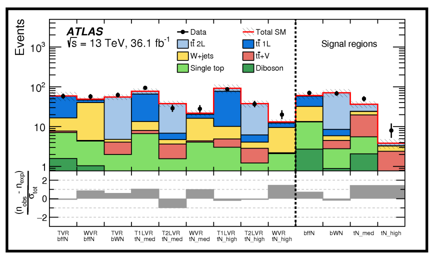
HistFactory

declarative binned likelihoods

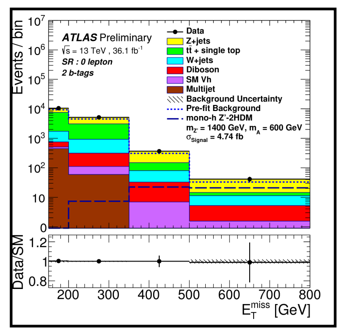
One of the most widely used statistical models in HEP for binned measuments and searches.



Standard Model



SUSY



Exotics

Mathematical Formulation:a parametrized p.d.f with parameters or interest (POI) and nuisance parameters

$$\mathcal{P}(n_c, x_e, a_p \,|\, \phi_p, \alpha_p, \gamma_b) = \boxed{\prod_{c\in\text{channels}} \left[\text{Pois}(n_c|\nu_c) \prod_{e=1}^{n_c} f_c(x_e|\alpha)\right]} \boxed{G(L_0|\lambda, \Delta_L) \cdot \prod_{p\in\mathbb{S}+\Gamma} f_p(a_p|\alpha_p)} \quad (1)$$

Primary Measurment:

- **multiple disjoint "channels" (e.g. event observables), each with multiple bins**
- **Poisson with rate parameters as functions of poi and nuisance parameters**

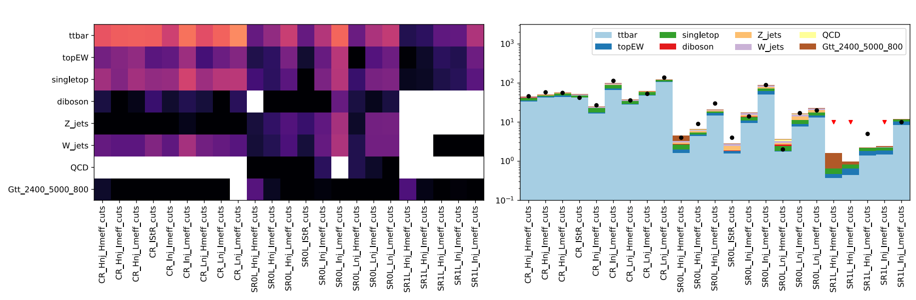
Auiliary Measurement

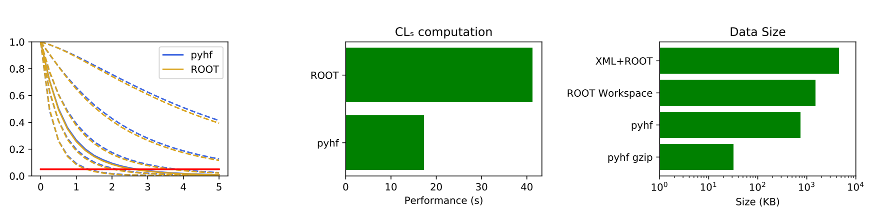
- **constraint terms on modeled as "measurements" of auxiliary data**

Performance

fast likelihood computation

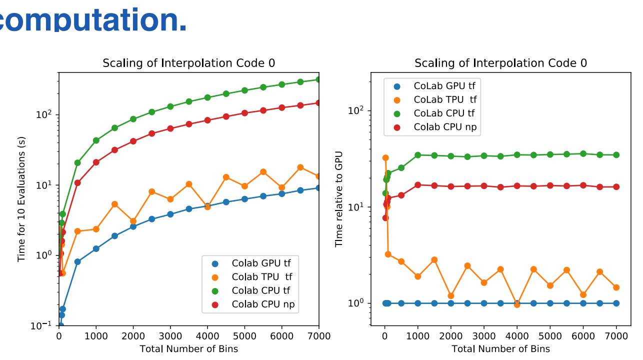
efficient use of tensor computation makes pyhf fast. Competitive with ROOT implementation - often faster.





Hardware Acceleration

For ML-library tensor backends Computational graph can be transparently placed on hardware accelerators: GPUs and TPUs for order of magnitude speed-up in computation.



Sharable Likelihoods

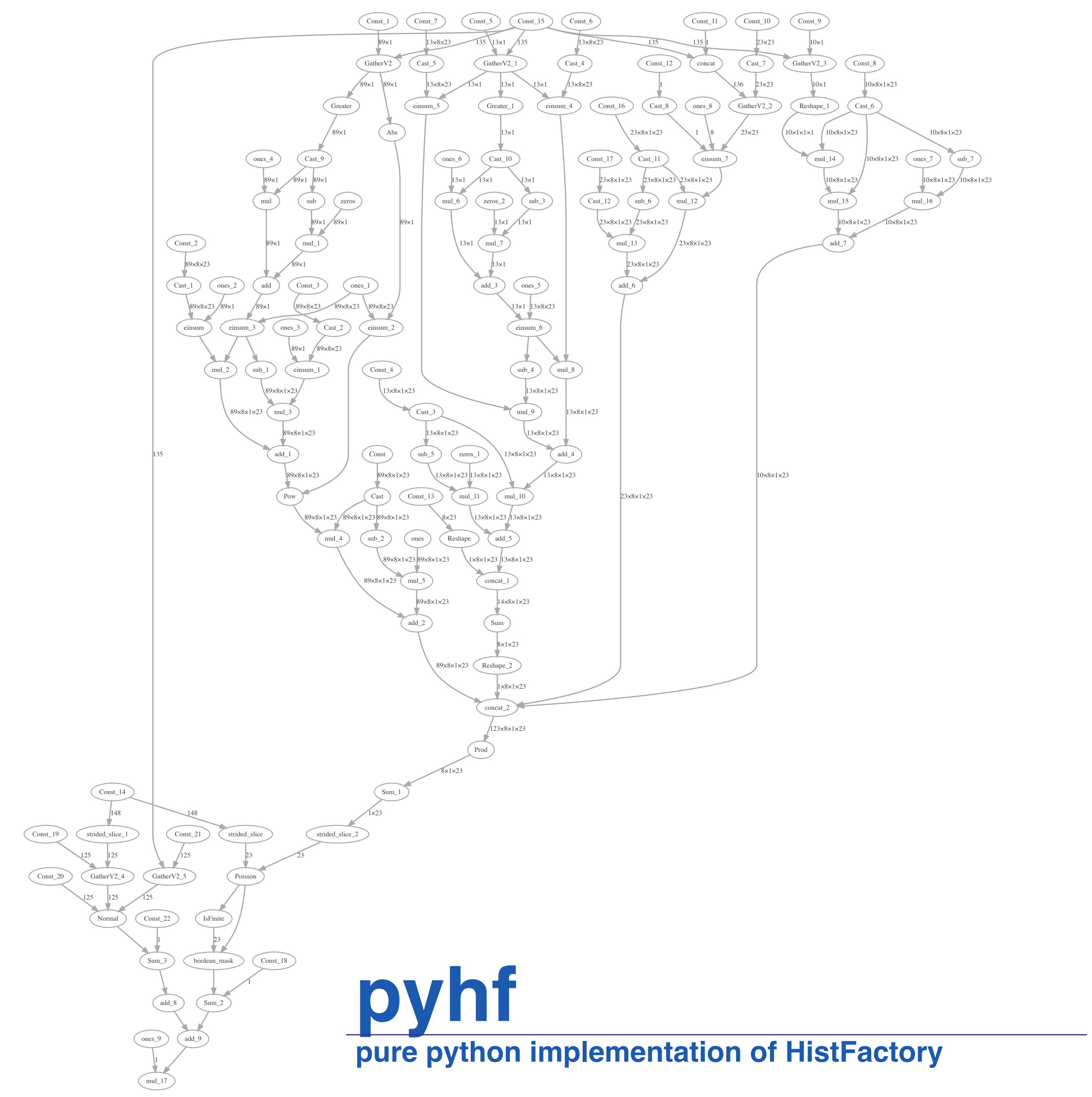
built for reinterpretation

For reinterpretation of searches, the bulk of the likelihood is invariant. Only need to patch the likelihood. Use JSONPatch standard to inject the new signal.

```
[
    {"op": "replace", "path": "/channels/0/samples/0/data", "value": [5., 6.]}
]
```

```
$> pyhf cls original.json|jq .CLs_obs
0.05290116065118097
```

```
$> pyhf cls original.json --patch newsignal.json|jq .CLs_obs
0.3401578753020146
```



pyhf

pure python implementation of HistFactory

implementation of HistFactory likelihood (1) as a computational graph of multi-dimensional array operations.

Use of array ("tensor") operations through a common API layer around high-performance tensor libraries: e.g.

NumPy TensorFlow PyTorch

Installation:

```
$> pip install pyhf
```

Example: simple number-counting experiment

```
import pyhf
pdf = pyhf.simplemodels.hepdata_like(
  signal_data=[12.0, 11.0], bkg_data=[50.0, 52.0], bkg_uncerts=[3.0, 7.0]
)
CLs_obs, CLs_exp = pyhf.utils.hypotest(1.0, [51, 48] + pdf.config.auxdata, pdf, return_expected=True)


print('Observed: {}, Expected: {}'.format(CLs_obs, CLs_exp))
Observed: [0.05290116], Expected: [0.06445521]
```

Auto-Differentiation:

Tensor libraries from ML communty provide exact gradients for use in minimization.

$$\frac{\partial\mathcal{L}}{\partial\mu}, \frac{\partial\mathcal{L}}{\partial\theta_i}$$

Optimizers

pyhf likeliehood are simple tensor-value python functions. Can use multiple minimization algorithms, such as `scipy.minimize` or MINUIT

JSON Format

The full likelihood can be expressed as a single JSON document

- **easy archivability (HepData)**
- **easy sharing across network**
- **easy manipulation**

```
$> curl http://url-to-json/workspace.json|pyhf cls
{
    "CLs_exp": [
        0.002606408505279359,
        0.013820656047622592,
        0.0644552079856191,
        0.23526102499555396,
        0.573041803728844
    ],
    "CLs_obs": 0.05290116065118097
}
```

```
toplvl:
  measurements:
  - {name: demo, config: {poi: mu}}
data:
  singlechannel: [51, 48]
channels:
- name: singlechannel
  samples:
  - name: signal
    data: [12, 11]
    modifiers:
    - name: mu
      type: normfactor
      data: null
  - name: background
    data: [50,52]
    modifiers:
    - name: uncorr_bkguncrt
      type: shapesys
      data: [3,7]
```