zfit

scalable pythonic fitting

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Scikit HEP affiliated

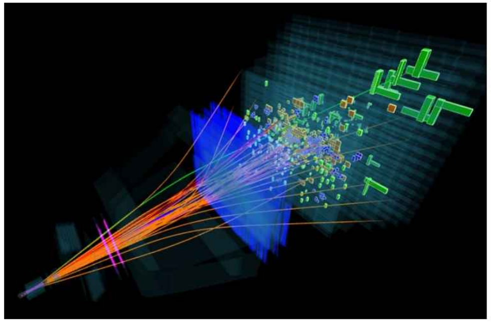
FNSNF Swiss National Science Foundation

University of Zurich UZH

Statistical inference in HEP

Analysis: from collecting data to extracting statistical statement

Reconstruction,
stripping, ...



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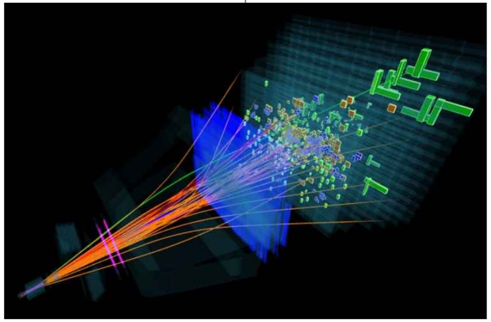
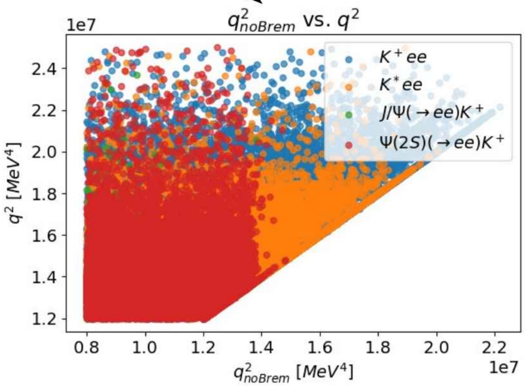




Statistical inference in HEP

Analysis: from collecting data to extracting statistical statement

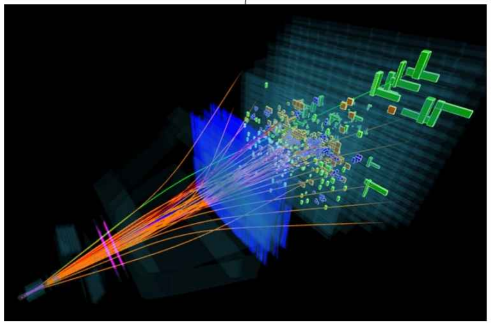
Involves often likelihood fitting and hypothesis testing

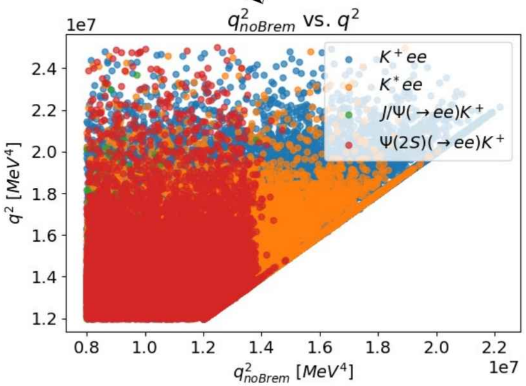
Reconstruction, stripping, ...

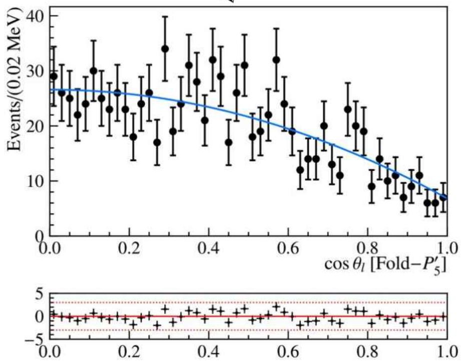
Selection, corrections, ...

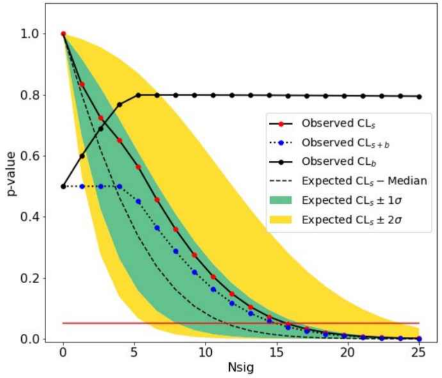
Model and fit

Hypothesis testing









Statistical inference in HEP

Analysis: from collecting data to extracting statistical statement

Involves often likelihood fitting and hypothesis testing

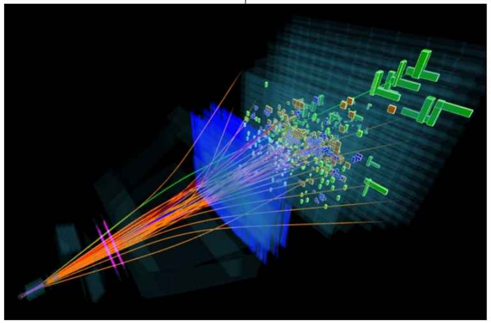
How to use Python for analysis?

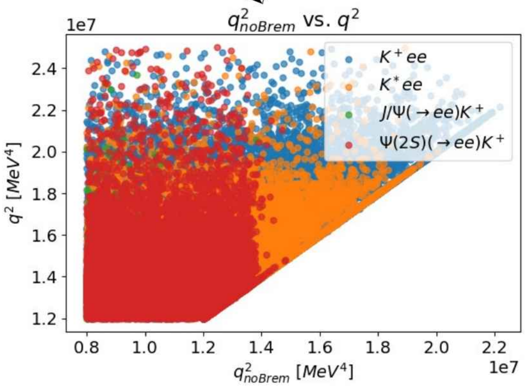
Reconstruction, stripping, ...

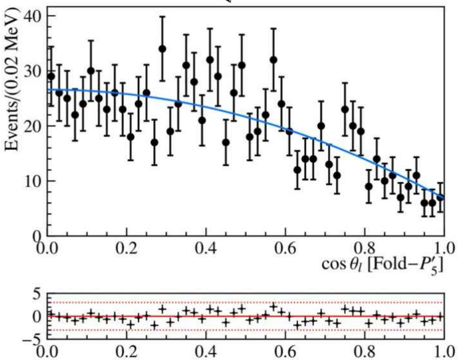
Selection, corrections, ...

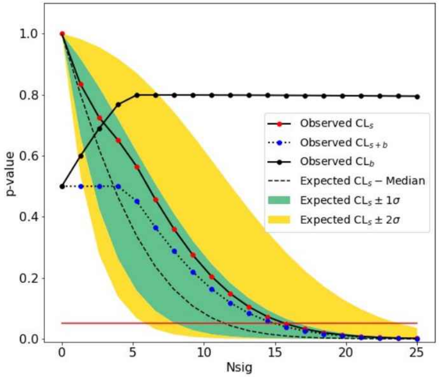
Model and fit

Hypothesis testing









Statistical inference in HEP

Analysis: from collecting data to extracting statistical statement

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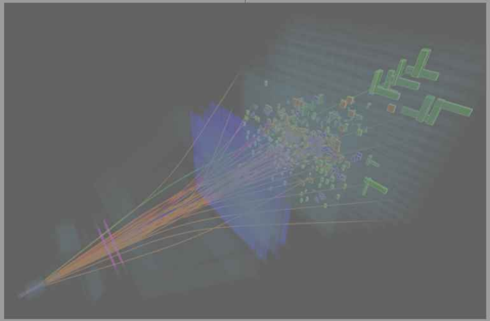

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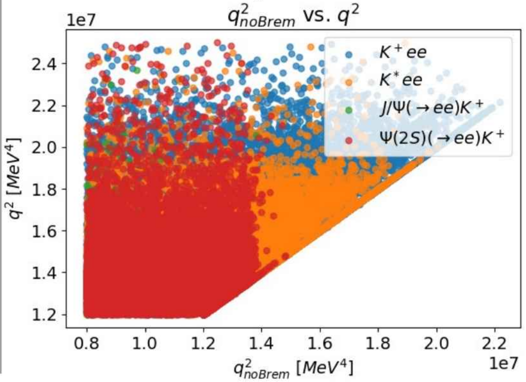
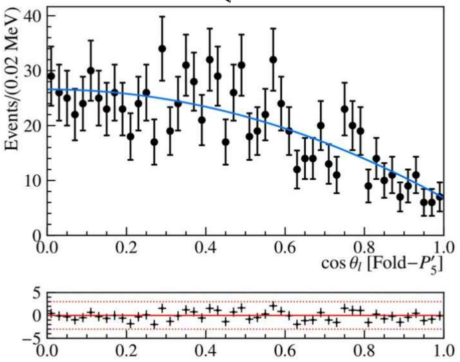
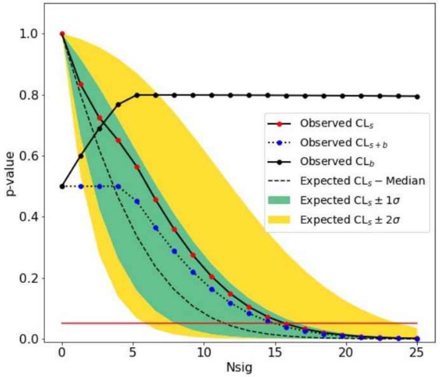


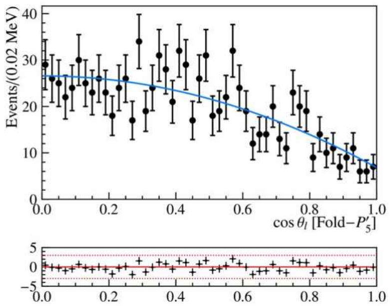
Model and fit



Hypothesis testing



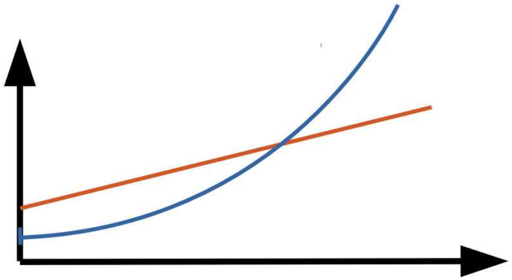
HEP Model Fitting in Python



HEP

advanced features, simply extendable

Scalable



large data, complex models

Pythonic

NumPy python™

integrate into ecosystem, stable API

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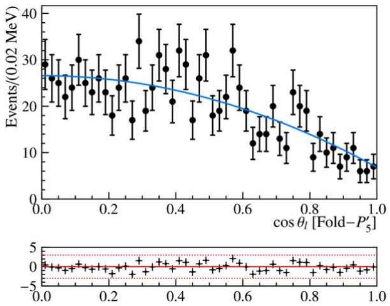

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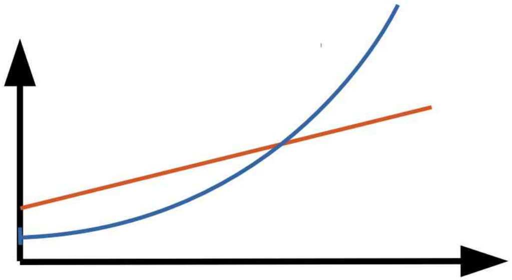

Scalable
large data, complex models

Pythonic
integrate into ecosystem, stable API

Complete fit

```python
normal_np = np.random.normal(2., 3., size=10_000)

obs = zfit.Space("x", limits=(-2, 3))

mu = zfit.Parameter("mu", 1.2, -4, 6)
sigma = zfit.Parameter("sigma", 1.3, 0.5, 10)
gauss = zfit.pdf.Gauss(mu=mu, sigma=sigma, obs=obs)

data = zfit.Data.from_numpy(obs=obs, array=normal_np)

nll = zfit.loss.UnbinnedNLL(model=gauss, data=data)

minimizer = zfit.minimize.Minuit()
result = minimizer.minimize(nll)

param_errors = result.hesse()
param_errors_asymmetric, new_result = result.errors()
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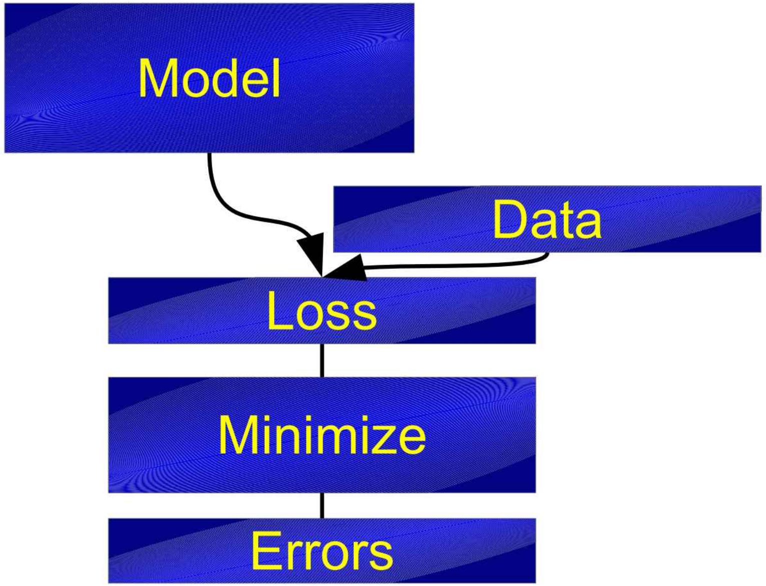

Complete fit: Model

```
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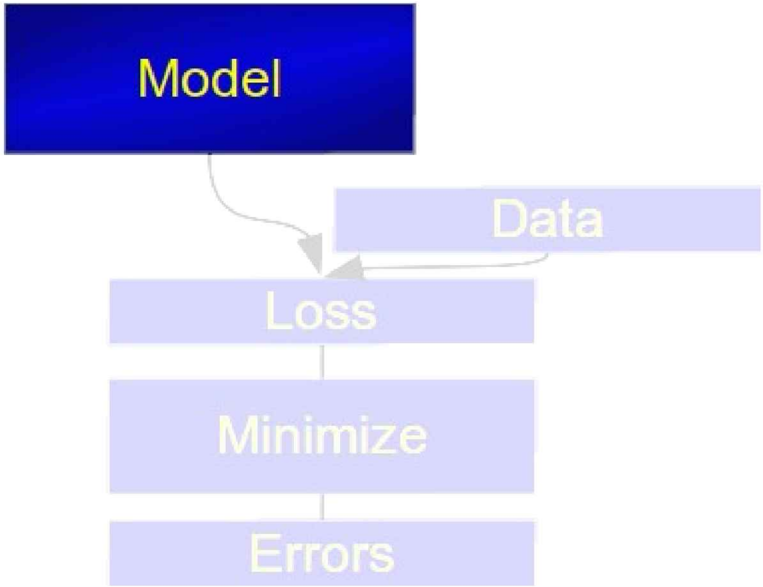

Complete fit: Data

```python
normal_np = np.random.normal(2., 3., size=10_000)

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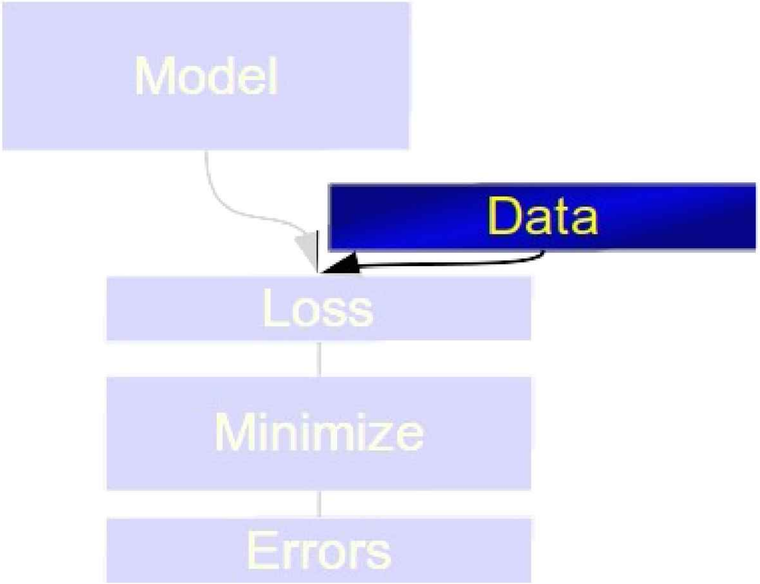

Complete fit: Loss

```python
normal_np = np.random.normal(2., 3., size=10_000)

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gauss = zfit.pdf.Gauss(mu=mu, sigma=sigma, obs=obs)

data = zfit.Data.from_numpy(obs=obs, array=normal_np)

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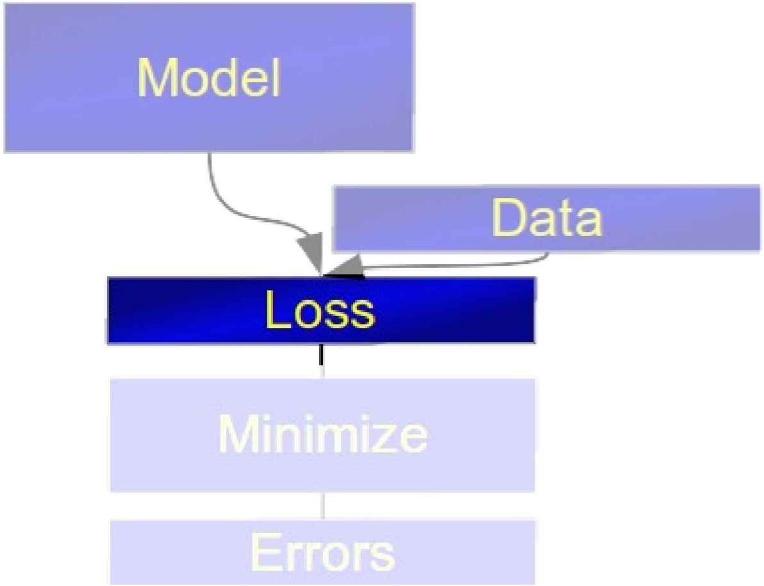

Complete fit: Minimization

```
normal_np = np.random.normal(2., 3., size=10_000)

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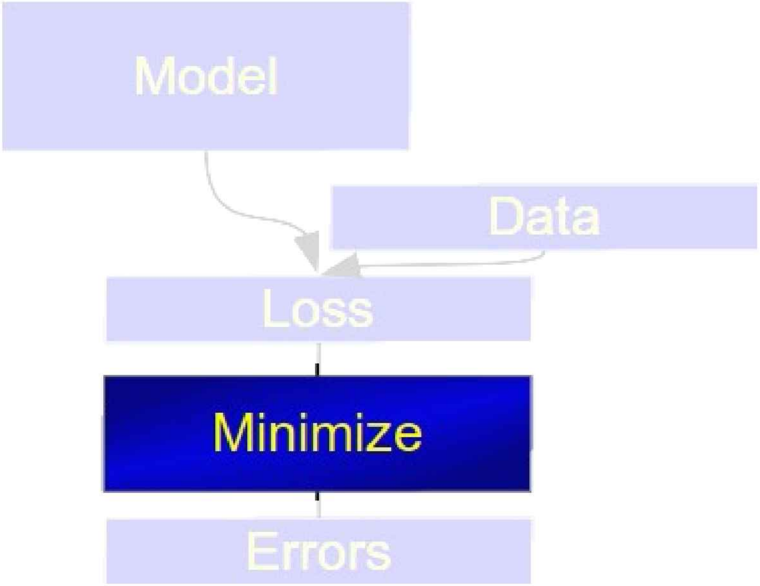

Complete fit: Result

```
normal_np = np.random.normal(2., 3., size=10_000)

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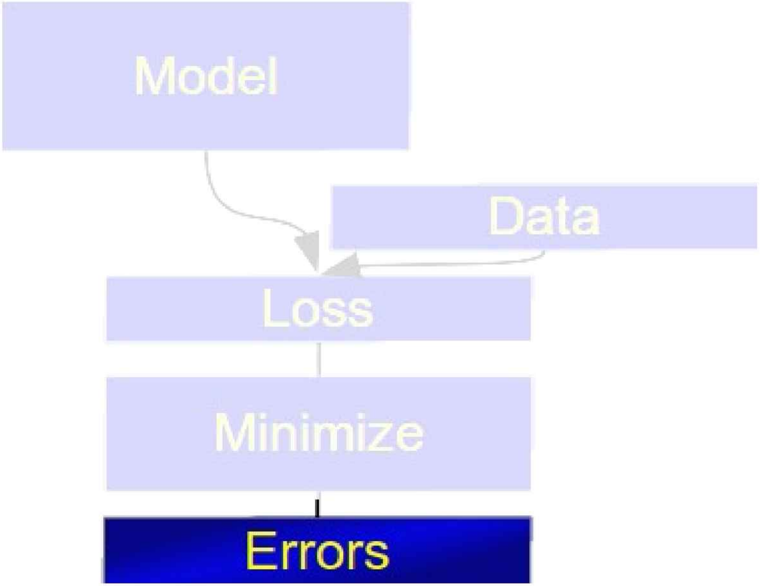

Basic API example

```
mu = zfit.Parameter("mu", 1.2, -4, 6)
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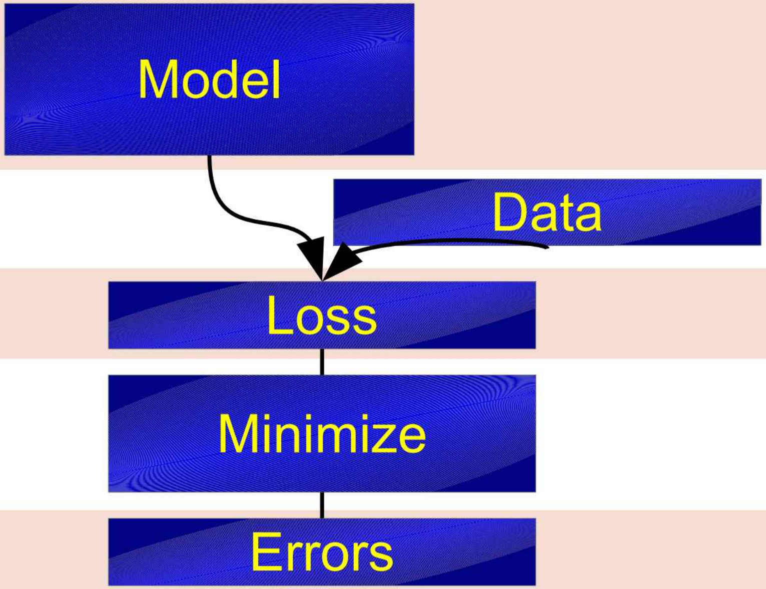
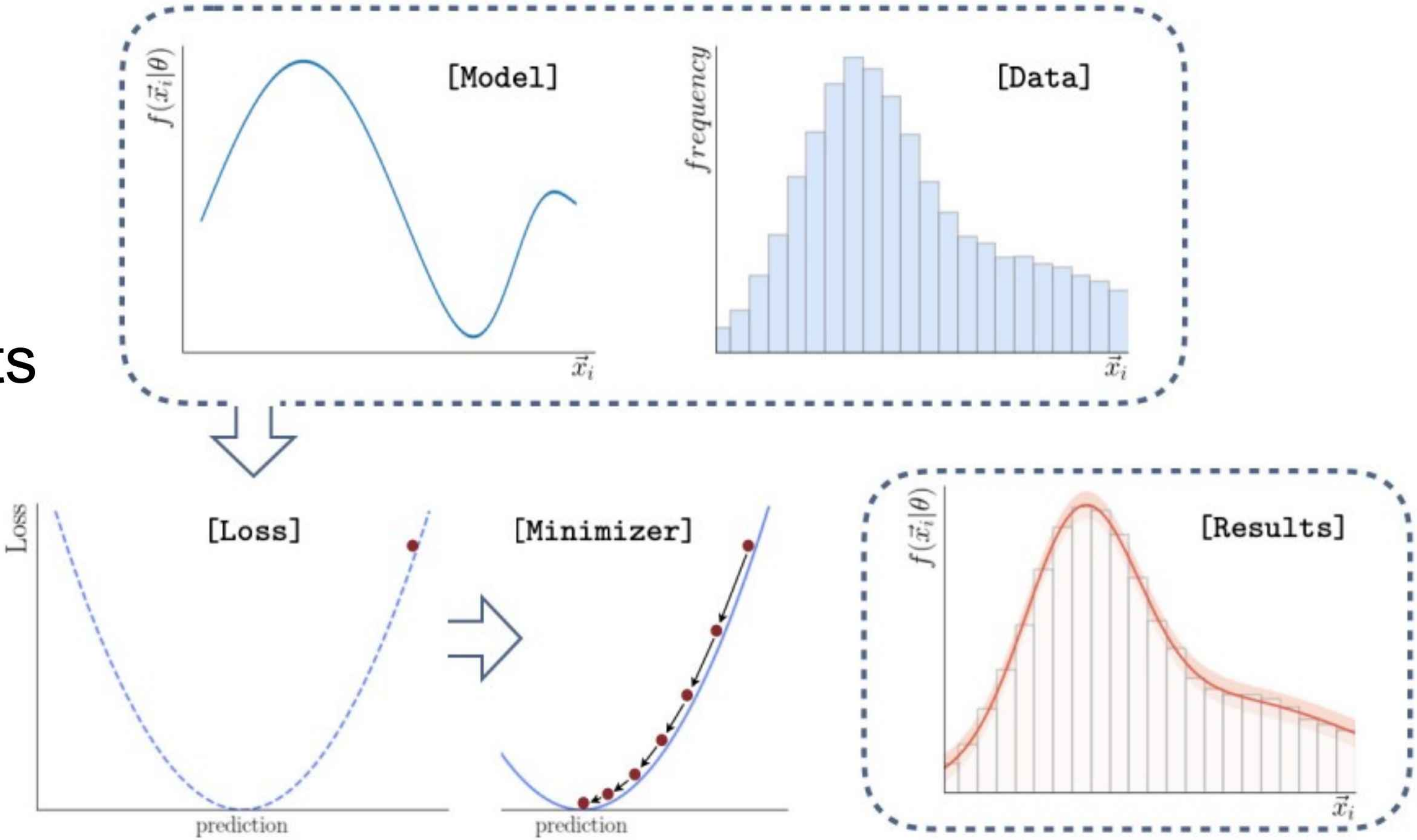


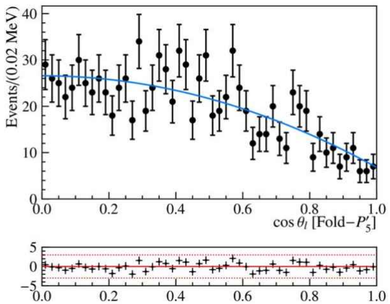
Workflow

Five maximally independent parts

"Fits look always
 the same"



HEP Model Fitting in Python



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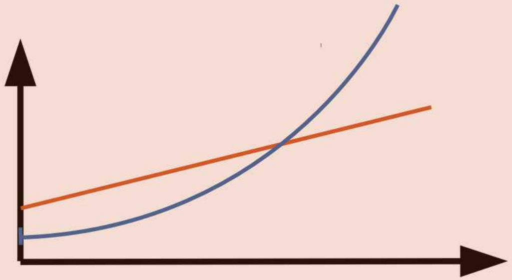


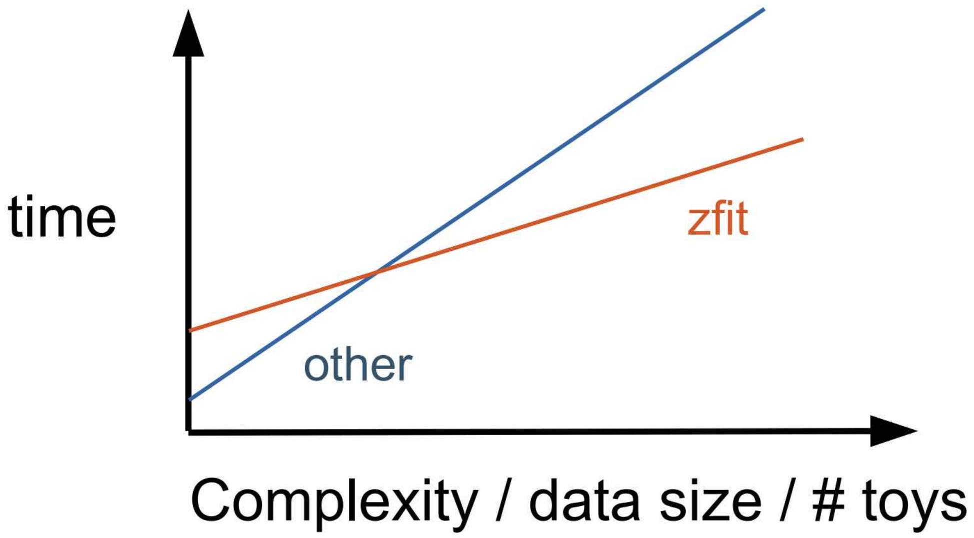
Scalable
large data, complex models

Pythonic
integrate into ecosystem, stable API

Scalable: Performance

There is no free lunch

- Initial overhead, flat increase
- TensorFlow (JAX, …) backend
- JIT compiled, CPU or GPU



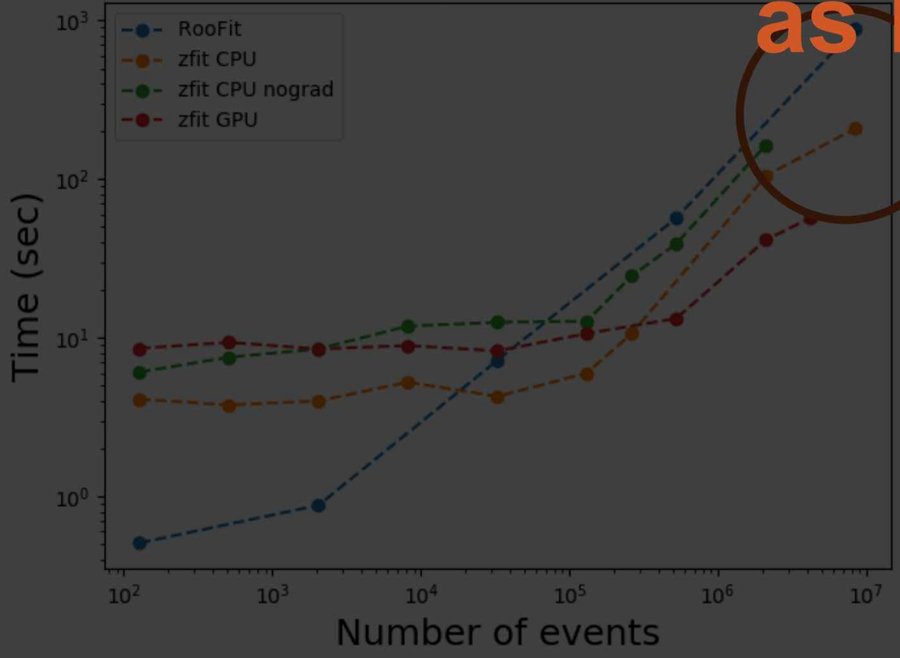
- Single, simple fit "slow"
  - 0.01 or 1 sec not relevant
  - 1 or 10 hours relevant

Scalable: Performance

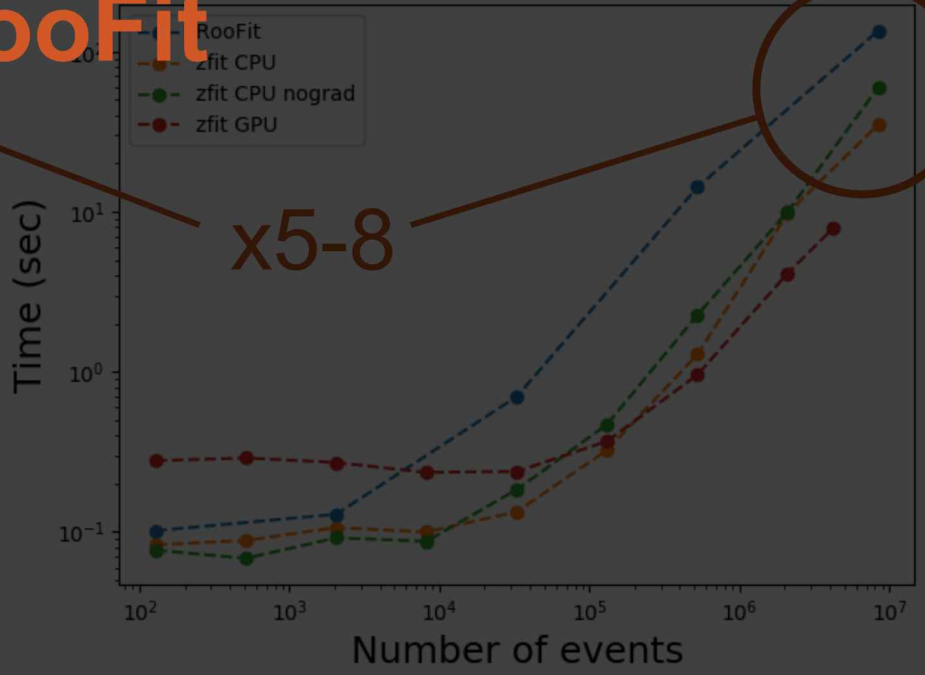
Sum of 9 Gaussians, toy fitting time, 6 core CPU: **RooFit** vs. **zfit**

Same order of magnitude as RooFit

9 free parameters



2 free parameters

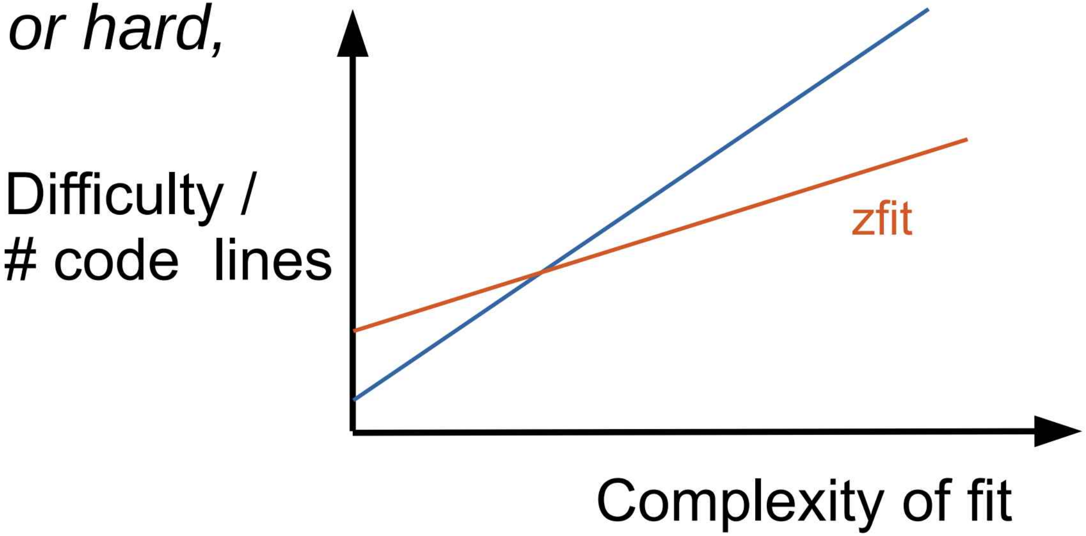


x5-8

Scalable: Usability

Things should not be easy or hard, but consistent

- Code lines
  - 5 or 10: irrelevant
  - 50 or 300: matters



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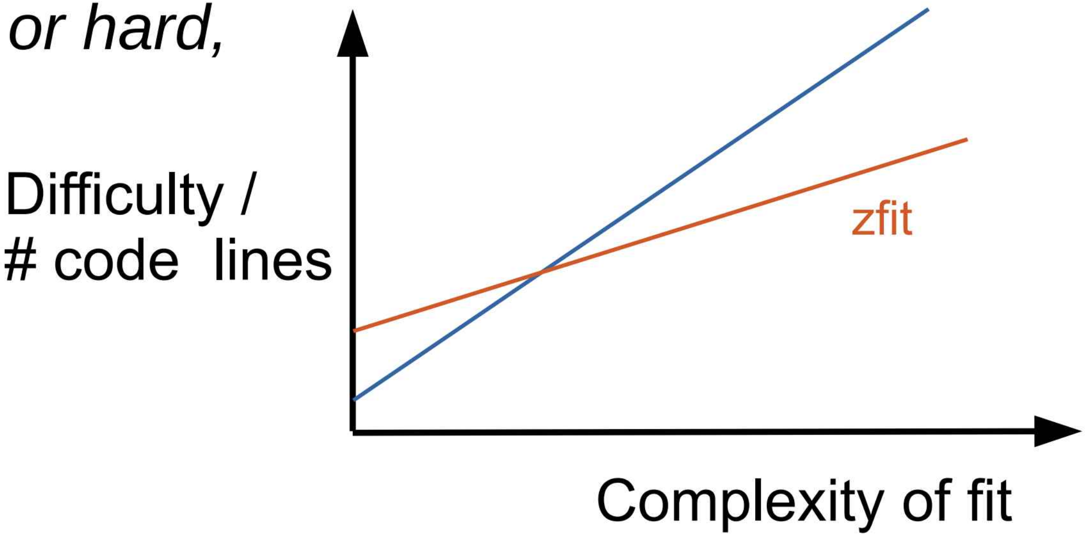
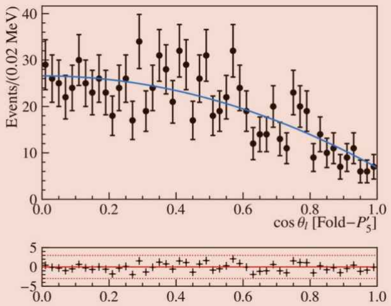


- Code lines
  - 5 or 10: irrelevant
  - 50 or 300: matters
- Cover all usecases out of the box is impossible
  - Convenient base classes, allow full control
  - Modular structure; provide all elements (e.g. shapes)

HEP Model Fitting in Python



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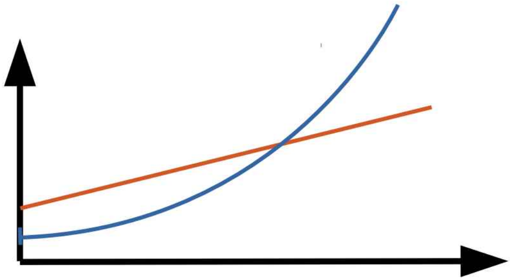

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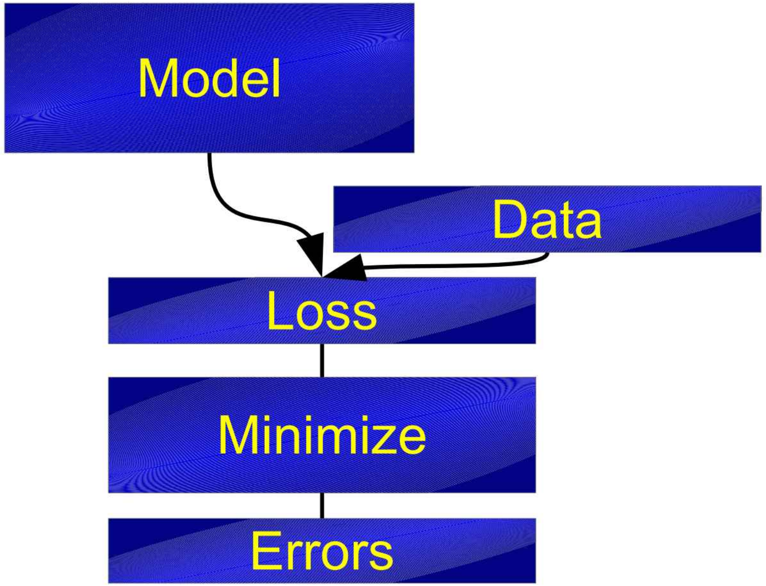

Complete fit: Model

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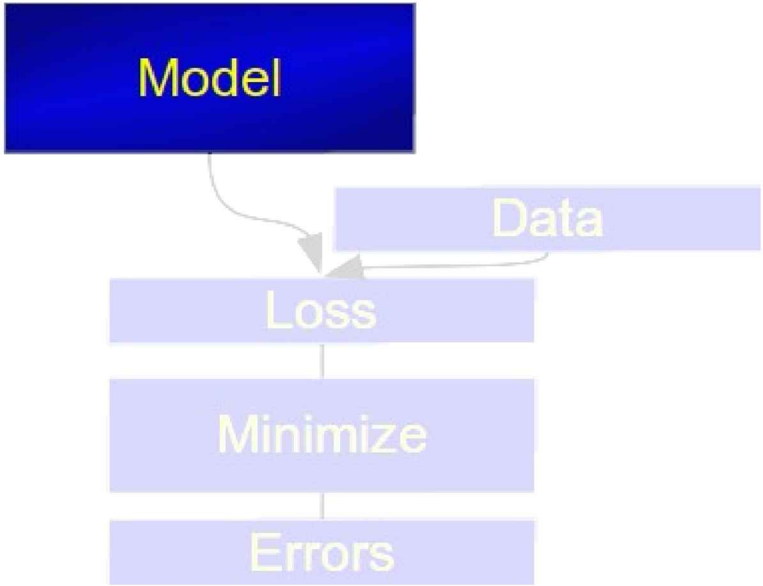
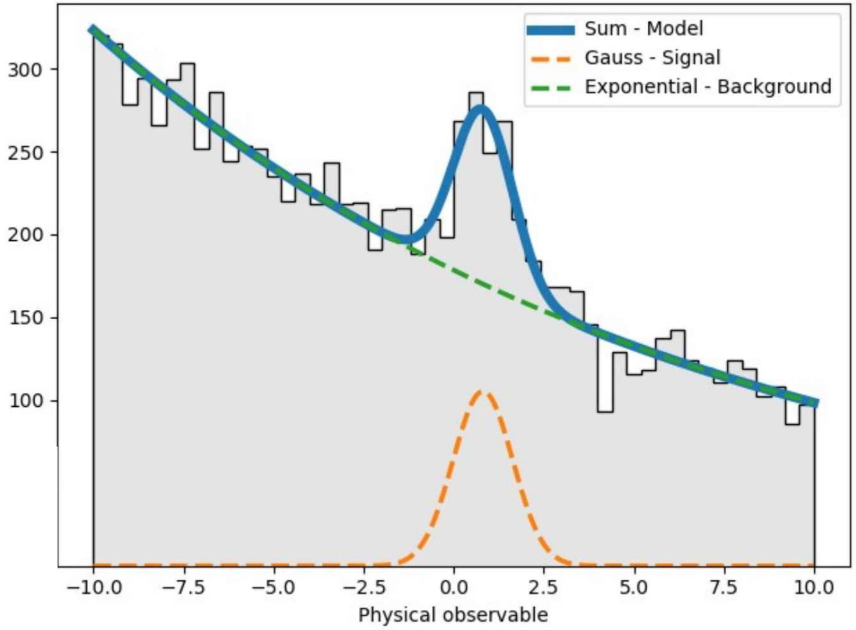


Example: Mass fit

- Sum, Product, *(Convolution)*
- Gauss, (double) Crystalball,...
- Exponential, Polynomials,…

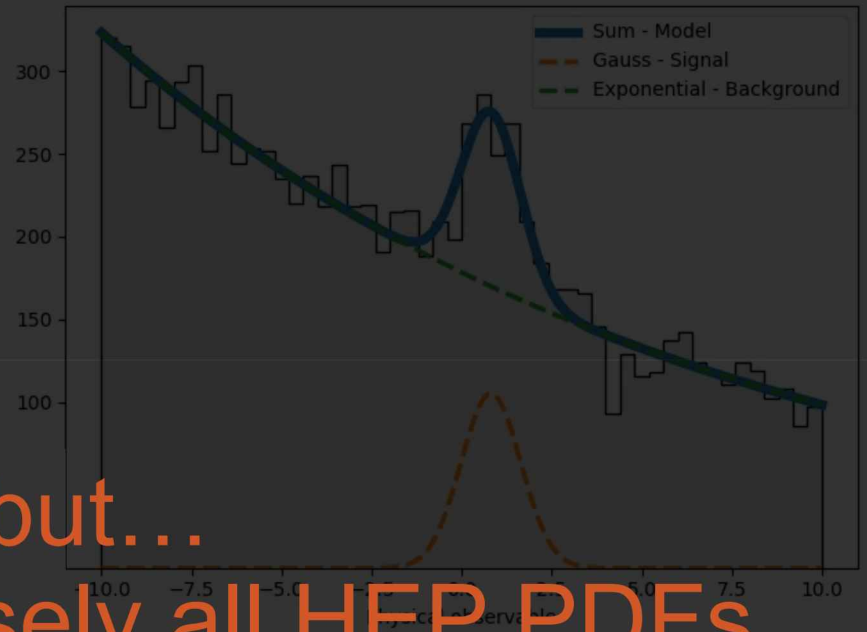



```
lambd = zfit.Parameter("lambda", -0.06, -1, -0.01)
frac = zfit.Parameter("fraction", 0.3, 0, 1)

gauss = zfit.pdf.Gauss(mu=mu, sigma=sigma, obs=obs)
exponential = zfit.pdf.Exponential(lambd, obs=obs)
model = zfit.pdf.SumPDF([gauss, exponential], fracs=frac)
```

Example: Mass fit

- Sum, Product, *(Convolution)*
- Gauss, (double) Crystalball,...
- Exponential, Polynomials,…

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exponential = zfit.pdf.Exponential(lambd, obs=obs)
model = zfit.pdf.SumPDF([gauss, exponential], fracs=frac)
```

Good for out-of-the-box but…
does not cover even closely all HEP PDFs

Custom PDF

```python
from zfit import z
from zfit.z import numpy as znp

class CustomPDF(zfit.pdf.ZPDF):
    _PARAMS = ['alpha']

    def _unnormalized_pdf(self, x):
        data = z.unstack_x(x)
        alpha = self.params['alpha']

        return znp.exp(alpha * data)
```

implement custom function

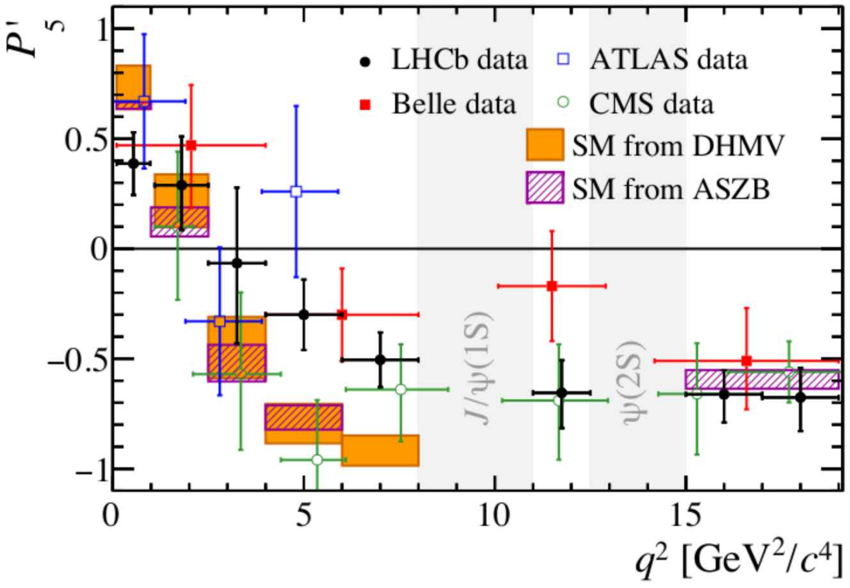
Custom PDF

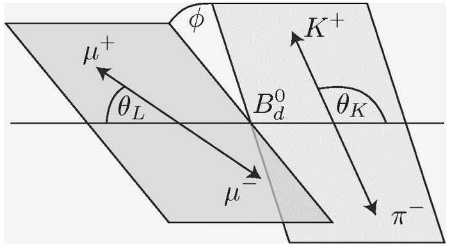
```python
from zfit import z
from zfit.z import numpy as znp

class CustomPDF(zfit.pdf.ZPDF):
    _PARAMS = ['alpha']

    def _unnormalized_pdf(self, x):
        data = z.unstack_x(x)
        alpha = self.params['alpha']

        return znp.exp(alpha * data)
```

```python
custom_pdf = CustomPDF(obs=obs, alpha=0.2)

integral = custom_pdf.integrate(limits=(-1, 2))
sample   = custom_pdf.sample(n=1000)
prob     = custom_pdf.pdf(sample)
```

use functionality of model

$B^0 \to K^{*0} l^+ l^-$ angular: P5'






```
class P5pPDF(zfit.pdf.ZPDF):
    _PARAMS = ['FL', 'AT2', 'P5p']
    _N_OBS = 3

    def _unnormalized_pdf(self, x):
        FL = self.params['FL']
        AT2 = self.params['AT2']
        P5p = self.params['P5p']
        costheta_l, costheta_k, phi = ztf.unstack_x(x)

        sintheta_k = tf.sqrt(1.0 - costheta_k * costheta_k)
        sintheta_l = tf.sqrt(1.0 - costheta_l * costheta_l)

        sintheta_2k = (1.0 - costheta_k * costheta_k)
        sintheta_2l = (1.0 - costheta_l * costheta_l)

        sin2theta_k = (2.0 * sintheta_k * costheta_k)
        cos2theta_l = (2.0 * costheta_l * costheta_l - 1.0)

        pdf = ((3.0 / 4.0) * (1.0 - FL) * sintheta_2k +
               FL * costheta_k * costheta_k +
               (1.0 / 4.0) * (1.0 - FL) * sintheta_2k * cos2theta_l +
               -1.0 * FL * costheta_k * costheta_k * cos2theta_l +
               (1.0 / 2.0) * (1.0 - FL) * AT2 * sintheta_2k *
               sintheta_2l * tf.cos(2.0 * phi) + tf.sqrt(FL * (1 - FL))
               * P5p * sin2theta_k * sintheta_l * tf.cos(phi))

        return pdf
```

P5': optimised observable

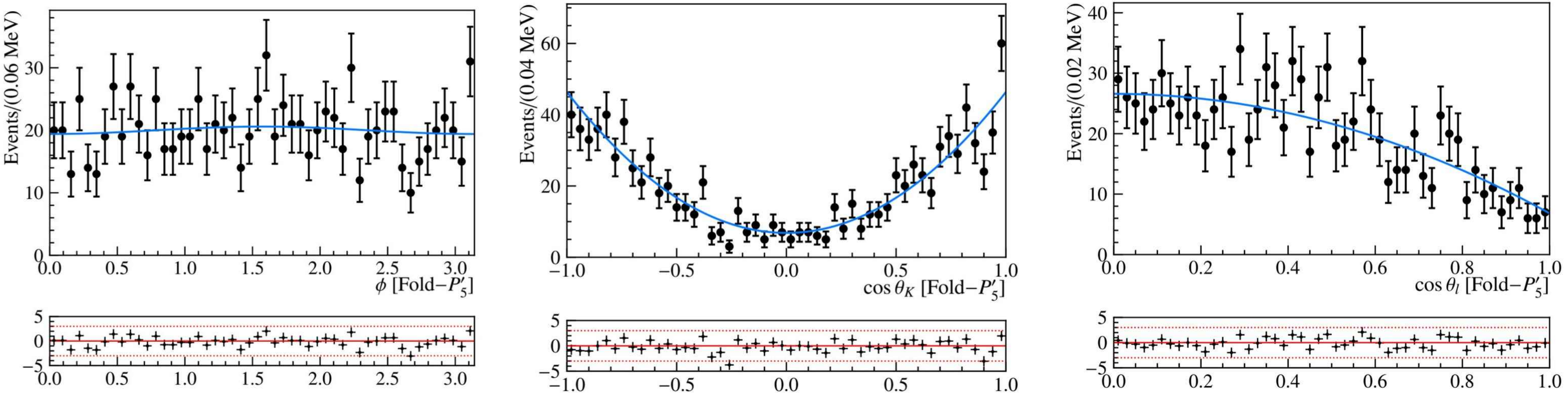
Fit of P5', from [1, 2]

[1] JHEP 02 (2016) 104 [2] Phys.Rev.Lett. 118 (2017) no.11, 111801

$B^0 \to K^{*0} l^+ l^-$ angular: fitted P5'

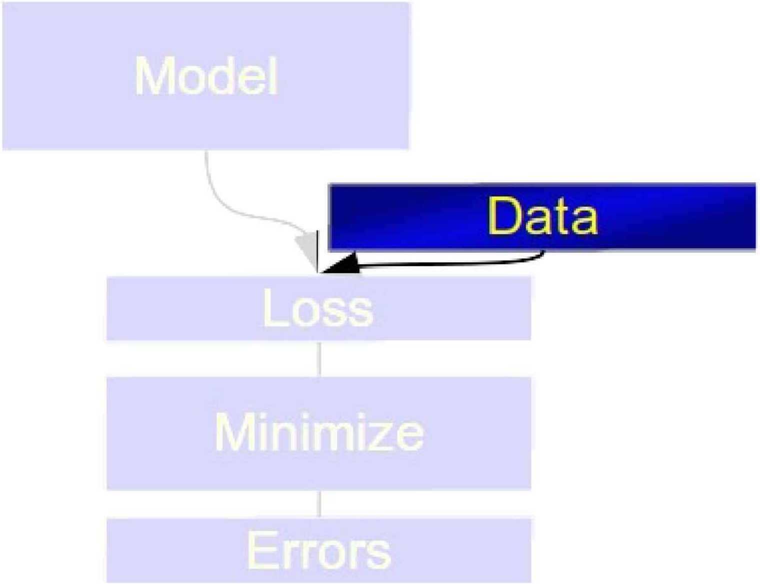
Projections of three angles

Plot with mplhep, matplotlib



Complete fit: Data

```python
normal_np = np.random.normal(2., 3., size=10_000)

obs = zfit.Space("x", limits=(-2, 3))

mu = zfit.Parameter("mu", 1.2, -4, 6)
sigma = zfit.Parameter("sigma", 1.3, 0.5, 10)
gauss = zfit.pdf.Gauss(mu=mu, sigma=sigma, obs=obs)

data = zfit.Data.from_numpy(obs=obs, array=normal_np)

nll = zfit.loss.UnbinnedNLL(model=gauss, data=data)

minimizer = zfit.minimize.Minuit()
result = minimizer.minimize(nll)

param_errors = result.hesse()
param_errors_asymmetric, new_result = result.errors()
```



Complete fit: Data

- From different sources
  - Numpy, Pandas, ROOT, …

Use the HEP/Python ecosystem for preprocessing

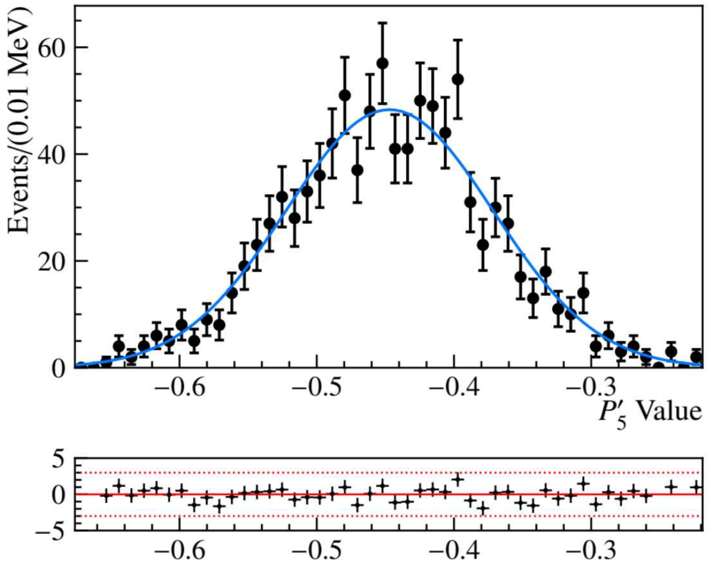
- Sampled from a model (toy studies)

```
data = model.create_sampler(n_sample, limits=obs)
```

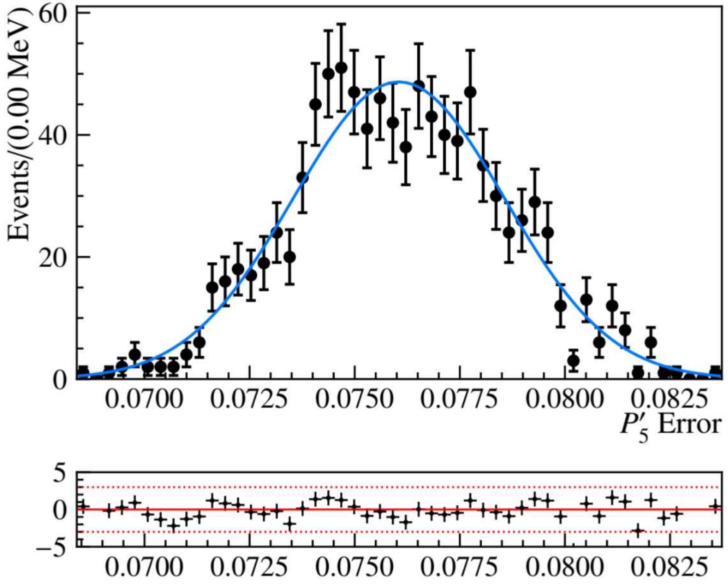
$B^0 \to K^{*0}l^+l^-$ angular: toy study

Result of toy study

P5' value

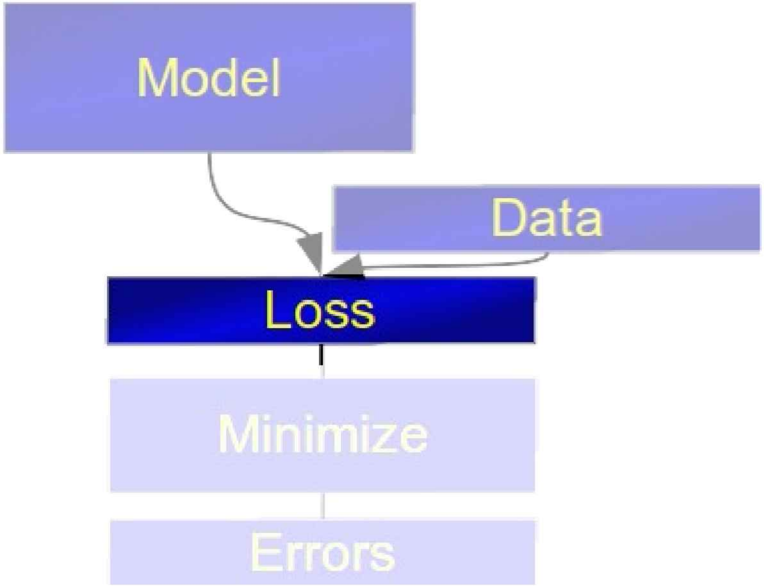


P5' error



Complete fit: Loss

```python
normal_np = np.random.normal(2., 3., size=10_000)

obs = zfit.Space("x", limits=(-2, 3))

mu = zfit.Parameter("mu", 1.2, -4, 6)
sigma = zfit.Parameter("sigma", 1.3, 0.5, 10)
gauss = zfit.pdf.Gauss(mu=mu, sigma=sigma, obs=obs)

data = zfit.Data.from_numpy(obs=obs, array=normal_np)

nll = zfit.loss.UnbinnedNLL(model=gauss, data=data)

minimizer = zfit.minimize.Minuit()
result = minimizer.minimize(nll)

param_errors = result.hesse()
param_errors_asymmetric, new_result = result.errors()
```



Loss

```python
mu_shared = zfit.Parameter("mu_shared", 1., -4, 6)
sigma1 = zfit.Parameter("sigma_one", 1., 0.1, 10)
sigma2 = zfit.Parameter("sigma_two", 1., 0.1, 10)

gauss1 = zfit.pdf.Gauss(mu=mu_shared, sigma=sigma1, obs=obs)
gauss2 = zfit.pdf.Gauss(mu=mu_shared, sigma=sigma2, obs=obs)
```

shared parameters

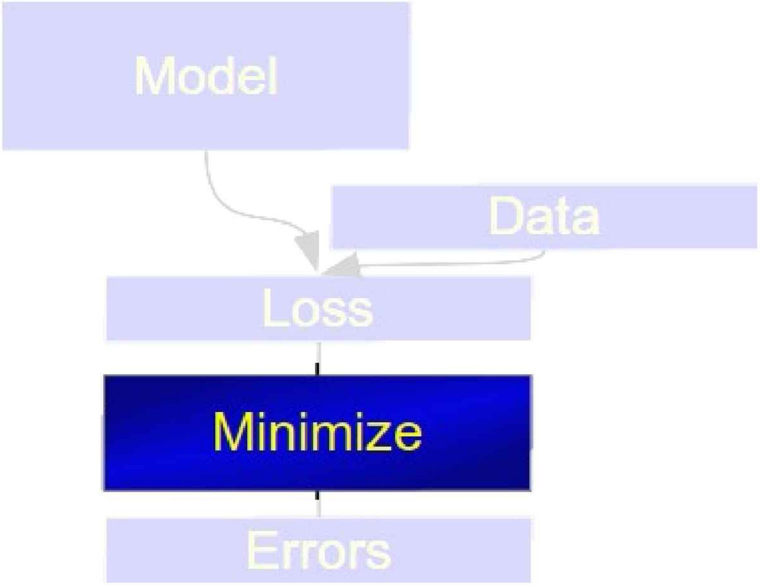
```python
nll_simultaneous = zfit.loss.UnbinnedNLL(model=[gauss1, gauss2],
                                         data=[data1, data2])

nll1 = zfit.loss.UnbinnedNLL(model=gauss1, data=data1)
nll2 = zfit.loss.UnbinnedNLL(model=gauss2, data=data2)
nll_simultaneous2 = nll1 + nll2
```

Completely equivalent

Constraints (also arbitrary) are fully supported

Complete fit: Minimization

```
normal_np = np.random.normal(2., 3., size=10_000)

obs = zfit.Space("x", limits=(-2, 3))

mu = zfit.Parameter("mu", 1.2, -4, 6)
sigma = zfit.Parameter("sigma", 1.3, 0.5, 10)
gauss = zfit.pdf.Gauss(mu=mu, sigma=sigma, obs=obs)

data = zfit.Data.from_numpy(obs=obs, array=normal_np)

nll = zfit.loss.UnbinnedNLL(model=gauss, data=data)

minimizer = zfit.minimize.Minuit()
result = minimizer.minimize(nll)

param_errors = result.hesse()
param_errors_asymmetric, new_result = result.errors()
```



Minimize

- Many different minimizers available, simply switch

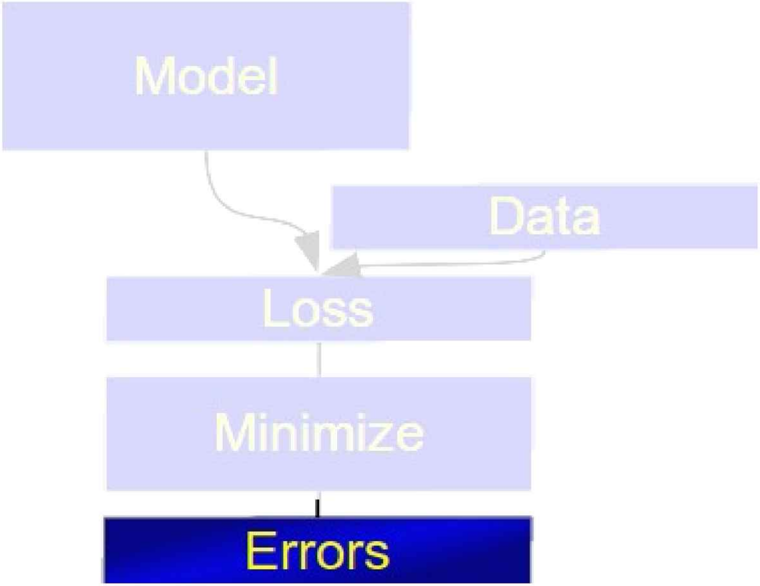
```
minimizer = zfit.minimize.IpyoptV1()
minimizer = zfit.minimize.Minuit()
minimizer = zfit.minimize.ScipyTrustConstrV1()
minimizer = zfit.minimize.NLoptLBFGSV1()
```

- Can use zfit loss, but also ***pure Python function***

```
result = minimizer.minimize(func, params)
```

Complete fit: Result

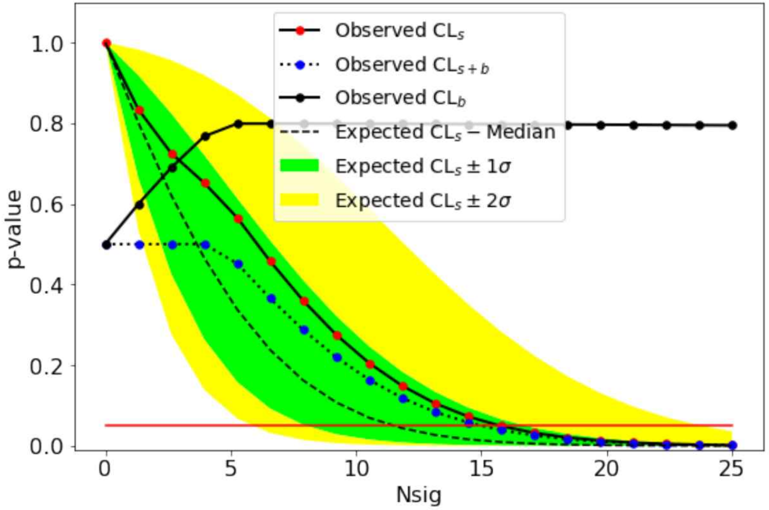
```
normal_np = np.random.normal(2., 3., size=10_000)

obs = zfit.Space("x", limits=(-2, 3))

mu = zfit.Parameter("mu", 1.2, -4, 6)
sigma = zfit.Parameter("sigma", 1.3, 0.5, 10)
gauss = zfit.pdf.Gauss(mu=mu, sigma=sigma, obs=obs)

data = zfit.Data.from_numpy(obs=obs, array=normal_np)

nll = zfit.loss.UnbinnedNLL(model=gauss, data=data)

minimizer = zfit.minimize.Minuit()
result = minimizer.minimize(nll)

param_errors = result.hesse()
param_errors_asymmetric, new_result = result.errors()
```



Back to HEP ecosystem: hepstats

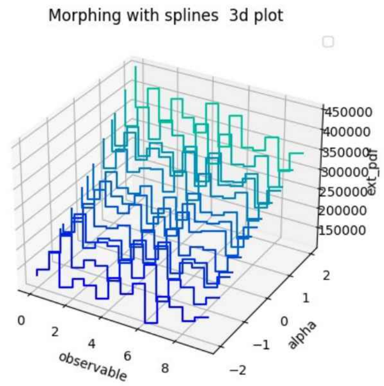
- High level statistics library for hypothesis tests
- Takes model, data, loss from zfit
- sWeights, CI, limits, …
  asymptotic or toys

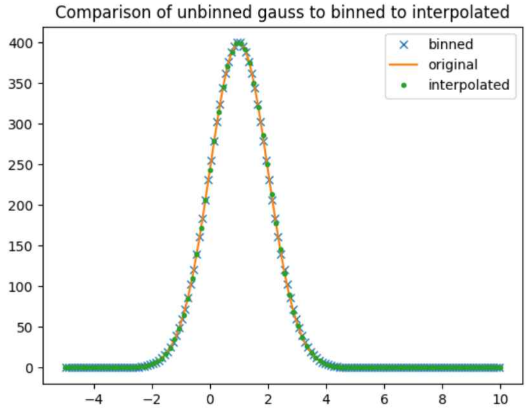
```
calculator = AsymptoticCalculator(loss, minimizer)
poinull = POIarray(Nsig, np.linspace(0.0, 25, 20))
poialt = POI(Nsig, 0)
ul = UpperLimit(calculator, poinull, poialt)
ul.upperlimit(alpha=0.05, CLs=True)
```

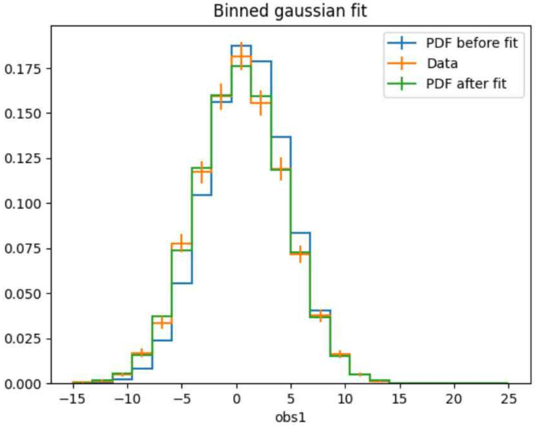


Close future: binned fits

- Integrate with boost_histogram, hist and mplhep
- Dedicated method "counts" (returns histogram)
- Features (expected):
  - Morphing of templates
  - Systematics of any kind
  - Interpolate (-> unbinned)
  - Irregular binning

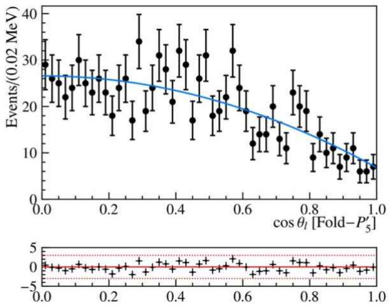


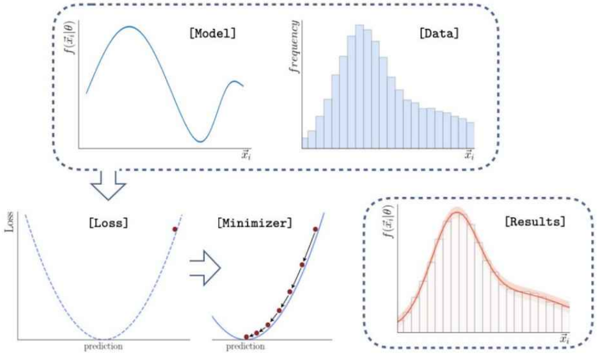




Expected in ~ 1 months:
Discussion welcome! Ideas? Use-cases?

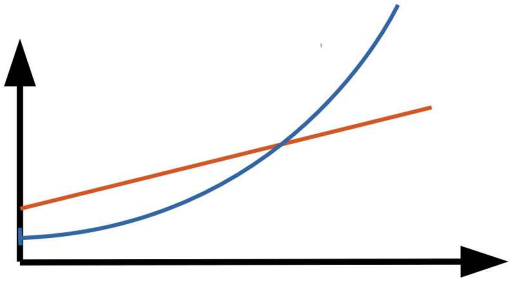
Conclusions





HEP

advanced features, simply extendable



Scalable

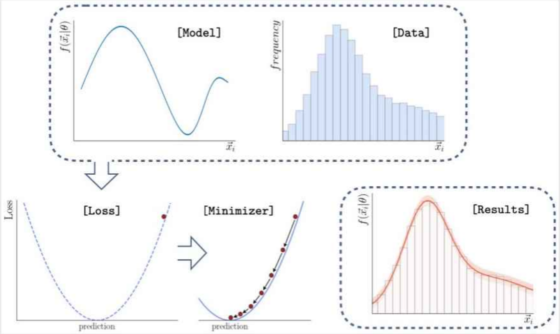
large data, complex models

Pythonic

integrate into ecosystem, stable API

scalable pythonic fitting

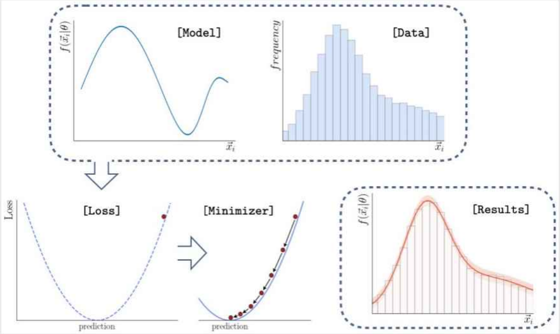
TensorFlow



zfit

scalable pythonic fitting

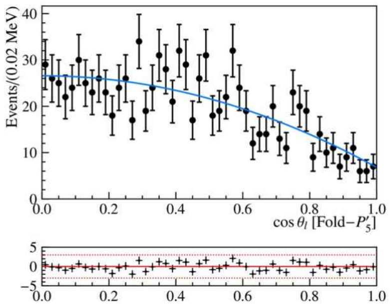
TensorFlow

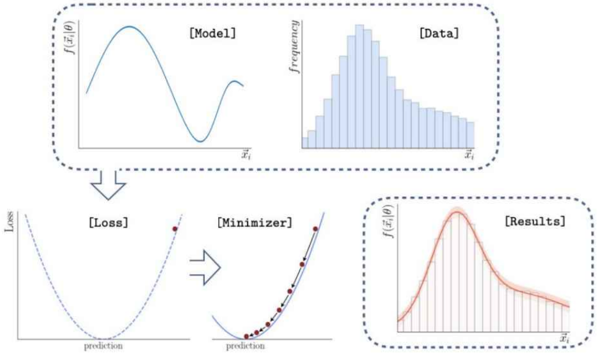


Try it out: https://github.com/zfit/zfit-tutorials

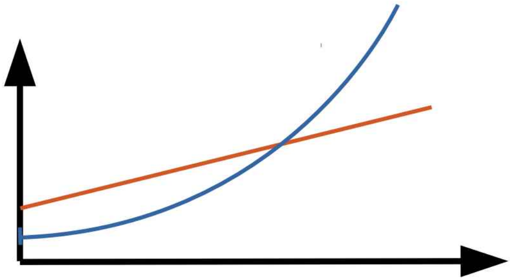
zfit

Conclusions





HEP
advanced features, simply extendable



Scalable
large data, complex models

Pythonic
integrate into ecosystem, stable API

Sources

- LHCb collision: https://physicsworld.com/wp-content/uploads/2018/08/LHCb-collision.png

Backup Slides

https://zfit.github.io/zfit/

zfit@GitHub

Gitter channel

zfit@physik.uzh.ch

Join the discussion!

- Backend & TF
- Amplitude
- K*ll toys
- K*mumu Wilson coeffs
- Other fitting packages
- Zfit (associated) packages
- Zfit project
- Zfit elements examples

Backend & TensorFlow

Backend: tracing and autograd

Tracing
execute Python once, remember (algebraic) computation

Autograd
"analytic" gradient of function

Recent rise of big data industry created libraries that support this

Includes GPU support, optimizations, caching,...

zfit: the project

build *the* stable model fitting ecosystem for HEP

- Integrate into HEP ecosystem

  functionality limited; stable API

- Technical requirements

  performance; maintainability

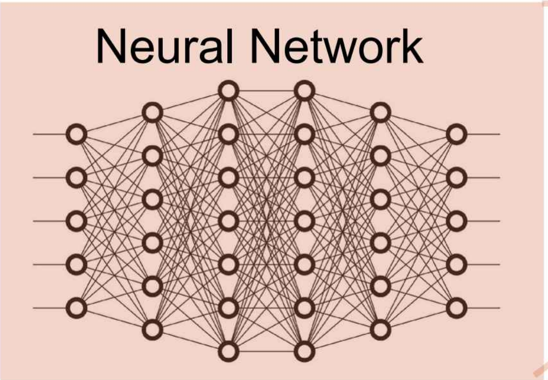
- HEP requirements

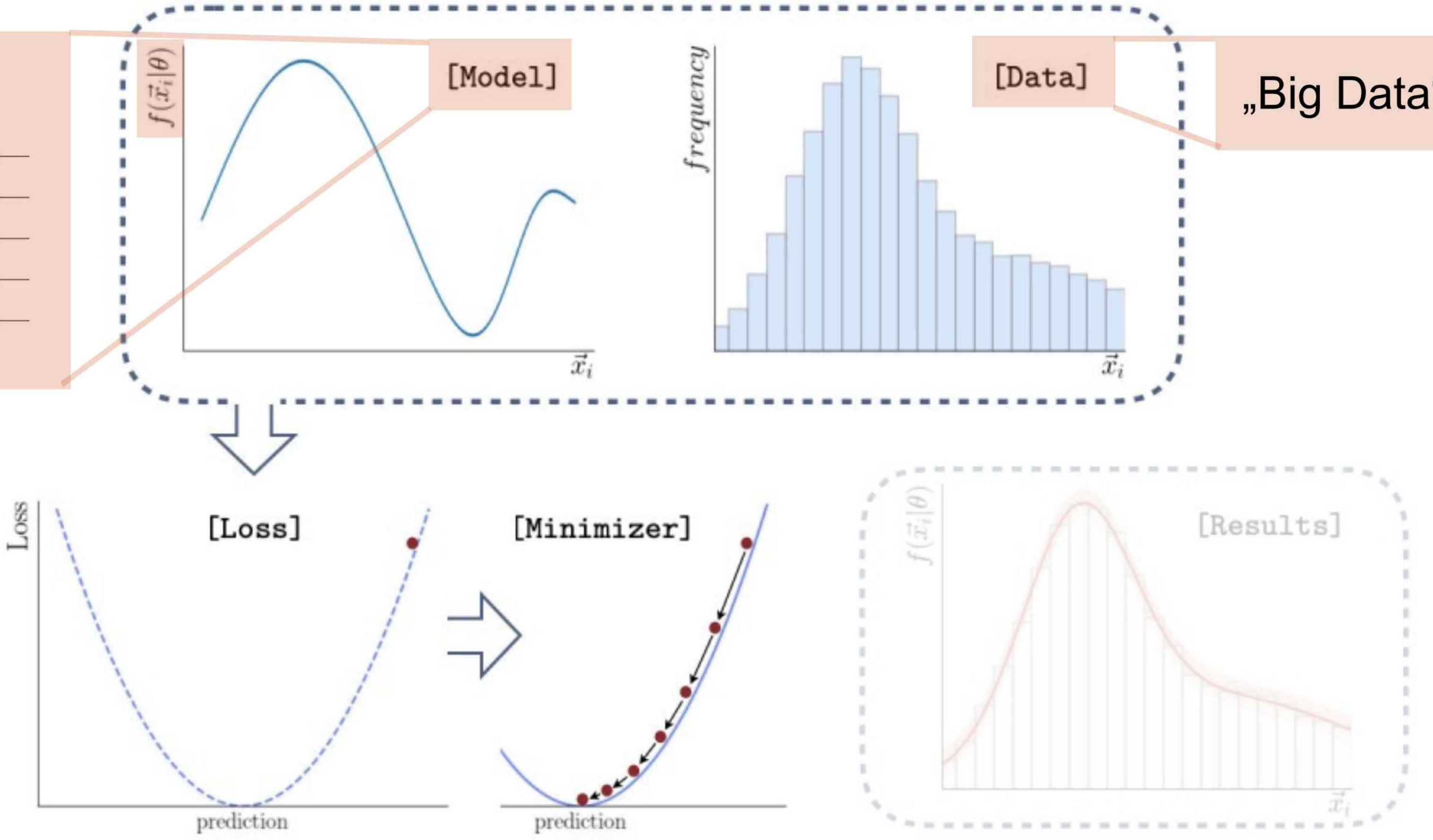
  advanced features; simply extendable code

Deep Learning

lessons for model fitting

Deep Learning





„Big Data“

„One huge, complicated function“

Main backend: TensorFlow

- By Google, highly popular (130k★, 4th on)
- Used in multiple physics libraries and analyses

Main backend: TensorFlow

- By Google, highly popular (150k★, 4th on)

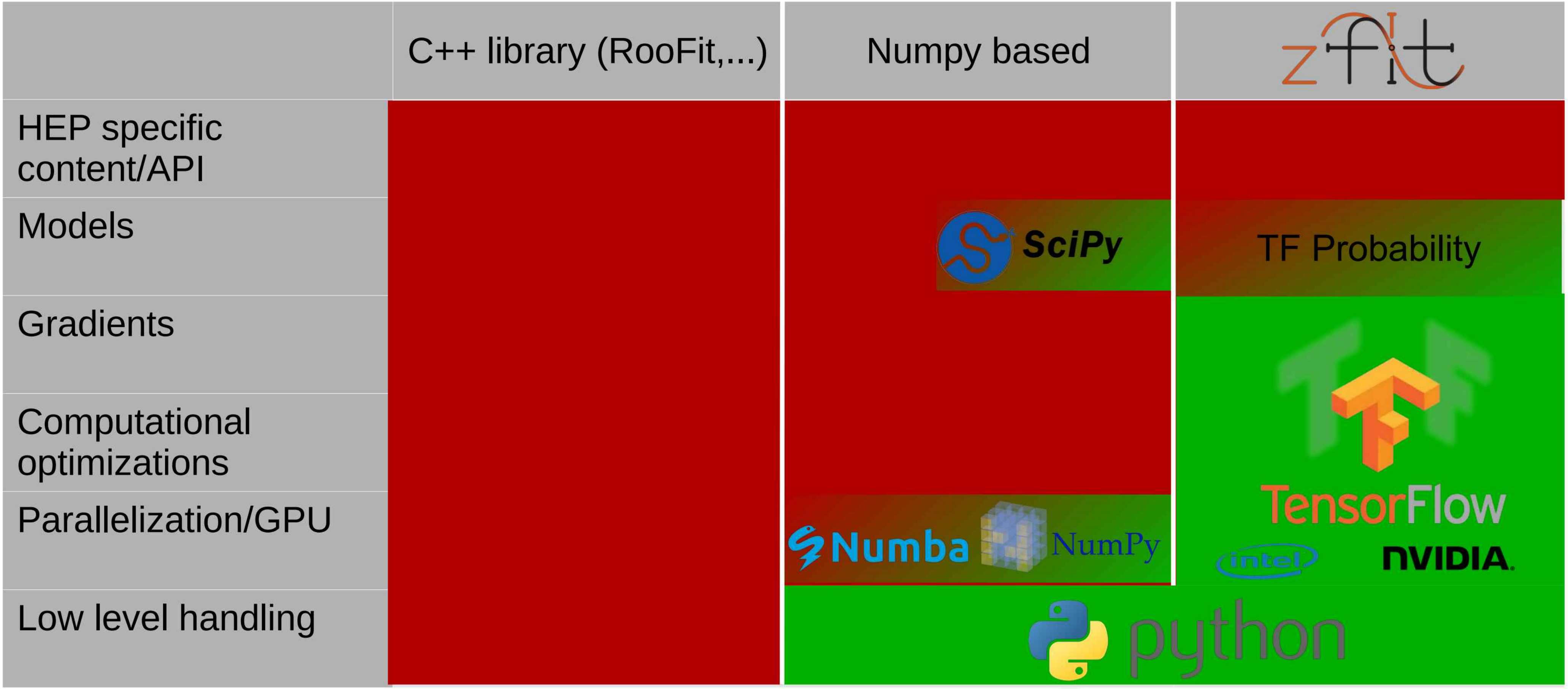
Main backend: TensorFlow

- By Google, highly popular (130k★, 4th on)
- Used in multiple physics libraries and analyses
- Consists of "two parts":
  - High level API for building neural networks *(NOT used!)*
  - Low level API with Numpy-style syntax

    tf.sqrt, tf.random.uniform,…
- Two modes:
  - "numpy"-like (full Python flexibility)
  - "compiled" (very performant)

GPU/Multi CPU support

Delegating the workload



Delegating the workload

	C++ library (RooFit,...)	Numpy based	zfit
HEP specific content/API			
Models		SciPy	TF Probability
Gradients			TensorFlow
Computational optimizations			TensorFlow
Parallelization/GPU		Numba NumPy	intel NVIDIA
Low level handling		python	python

"Stepping on the shoulders of a giant"

Delegating the workload

	C++ library (RooFit,...)	Numpy based	zfit
HEP specific content/API			API & Workflow
Models		SciPy	TF Probability
Gradients			TensorFlow
Computational optimizations			intel NVIDIA
Parallelization/GPU		Numba NumPy	
Low level handling		python	

Used & maintained (!) by industry

Can we express model fitting as static graphs?

Yes!

HPC perspective

1) Definition of computation, shape etc. (add static knowledge)
2) Compilation of the graph
3) Execution of computation (re-use optimized graph)

Inside TF, hidden to end-user

HPC: the more is know *before* the execution, the better

TensorFlow takes care of *how* to use this knowledge

Graph elements

… do not have to be constant!

Parameters

Can change their value

Random numbers

Generate newly on every graph execution: MC integration,…

Control flow (if, while)

Steer the execution: Accept-reject sampling (while), etc.

Static, not constant

Deep Learning vs. Model Fitting

Similarity	Complicated Models	Large Data	Composed loss	Minimization	Results and uncertainties
HEP	Non-trivial functions	Whole Dataset	simultaneous, constraints	Global min, 2nd derivative algorithm	Hesse, profiling
Deep Learning	Combine many, trivial functions	Many, small Batches	*Anything! (GANs, RL,...)*	Local (!) min, 1th derivative, many steps	None
Conclusion					

Deep Learning vs. Model Fitting

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Conclusion	No real impact	Optimizations for OOM calculations	HEP trivial special case	~~Optimizers~~ Free „analytic“ derivatives!	No support, but simple

But...

what ***is*** a Deep Learning library?

Deep Learning vs. Model Fitting

Similarity	Complicated Models	Large Data	Composed loss	Minimization	Results and uncertainties
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Deep Learning vs. Model Fitting

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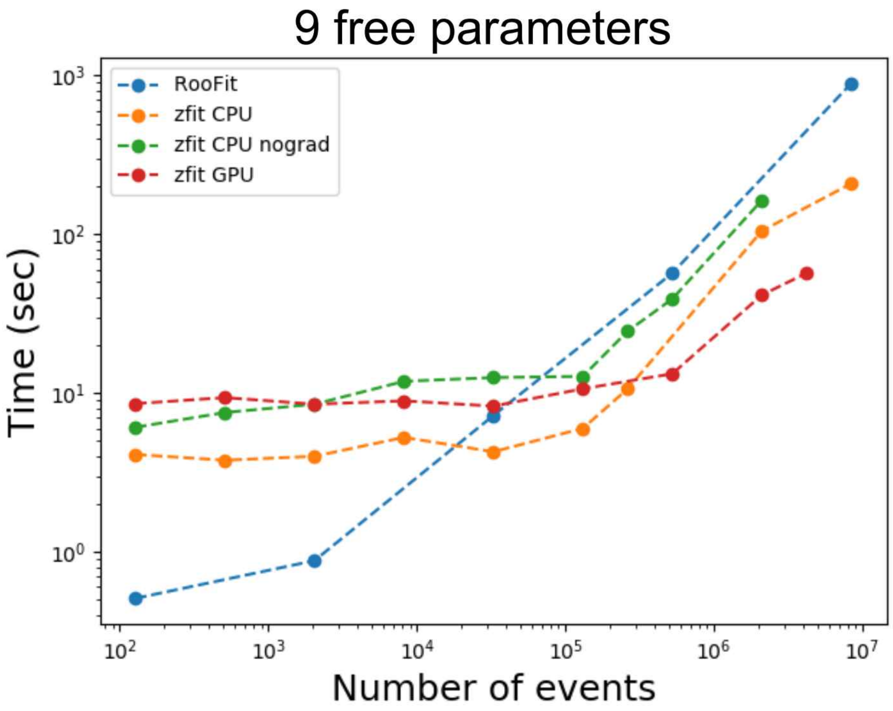
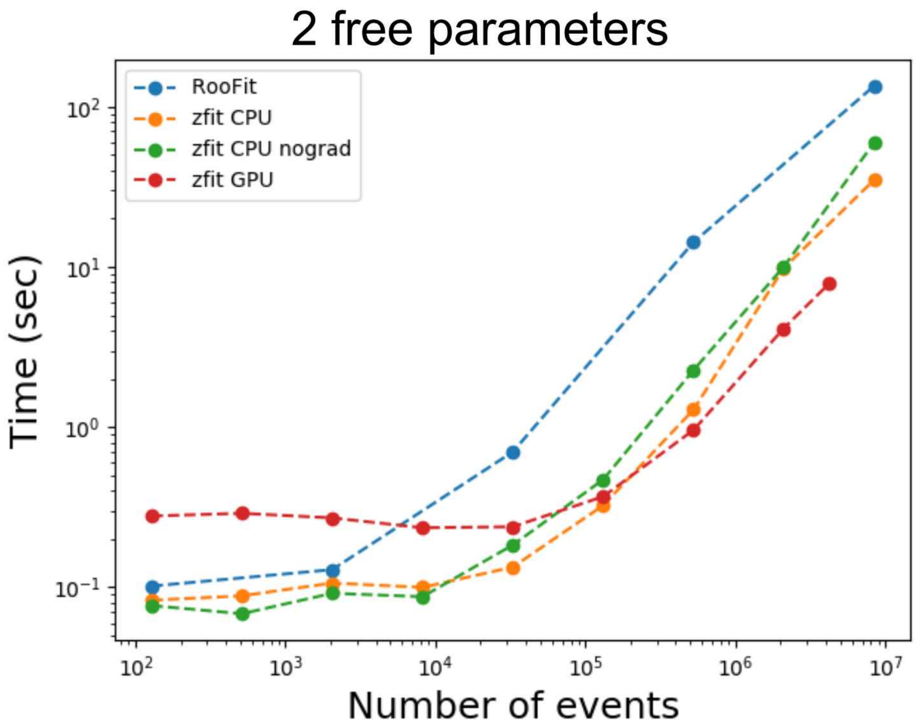
Modern, high performance computing

Scalability: Performance

Fitting time (lower is better): **RooFit** vs. **zfit**

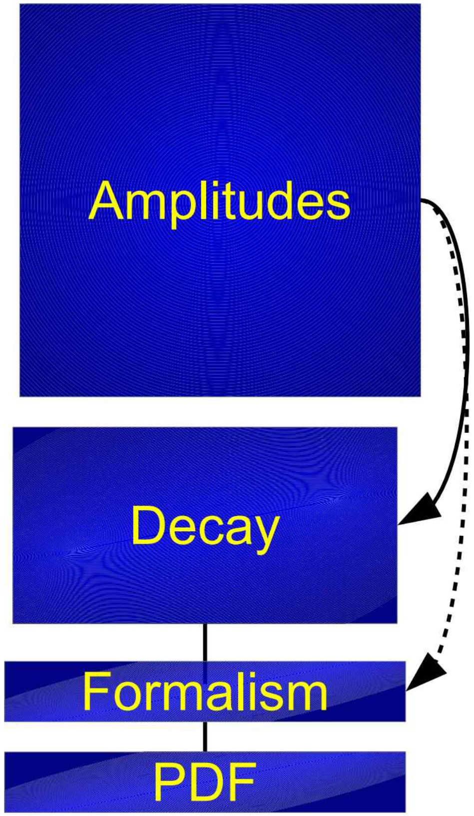




Amplitude

Example amplitude

```python
RESONANCES = [('rho(770)', ('pi-', 'pi0'), bw_amplitude),
              ('K(2)*(1430)0', ('K+', 'pi-'), bw_amplitude),
              ('K(0)*(1430)+', ('K+', 'pi0'), bw_amplitude),
              ('K*(892)+', ('K+', 'pi0'), bw_amplitude),
              ('K(0)*(1430)0', ('K+', 'pi-'), bw_amplitude),
              ('K*(892)0', ('K+', 'pi-'), bw_amplitude)]

COEFFS = {...}

D2Kpipi0 = Decay('D0', ['K+', 'pi-', 'pi0'])

for res, children, amp in RESONANCES:
    D2Kpipi0.add_amplitude(res, children, amp, COEFFS[res])

formalism = ThreeBodyDalitzFormalism("Zemach B Frame")

pdf = D2Kpipi0.create_pdf(name="D2Kpipi0", formalism=formalism)
```



Angular toys

$B^0 \to K^{*0} l^+ l^-$ angular: toy study

Sensitivity study

- draw toys (sample) from PDF
- Fit to sample

```
for i in range(ntoys):

    # set initial sampling values
    for param in params:
        param.set_value(...)

    sampler.resample()

    # set random initial values
    for param in params:
        param.set_value(...)

    result = minimizer.minimize(nll)

    if result.converged:
        ...
```

$\mathrm{B}^0 \to K^{*0} l^+ l^-$ angular: toys

Sensitivity study

- draw toys (sample) from PDF
- Fit to sample

```
for i in range(ntoys):

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    result = minimizer.minimize(nll)

    if result.converged:
        ...
```
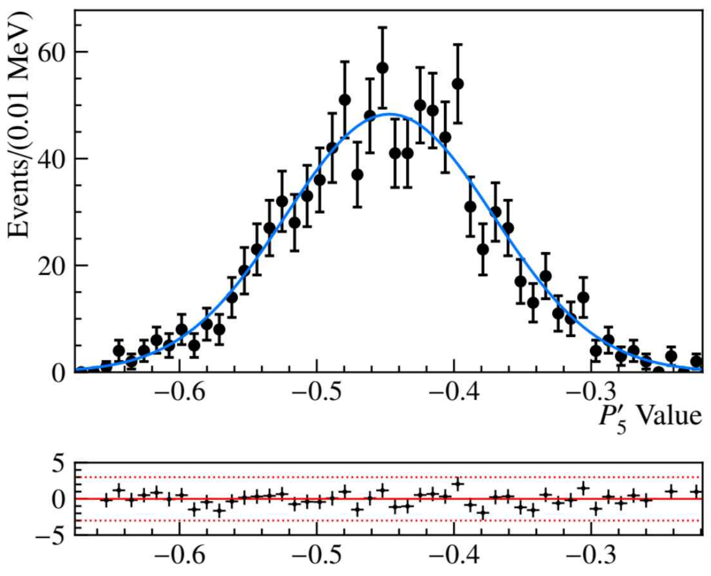
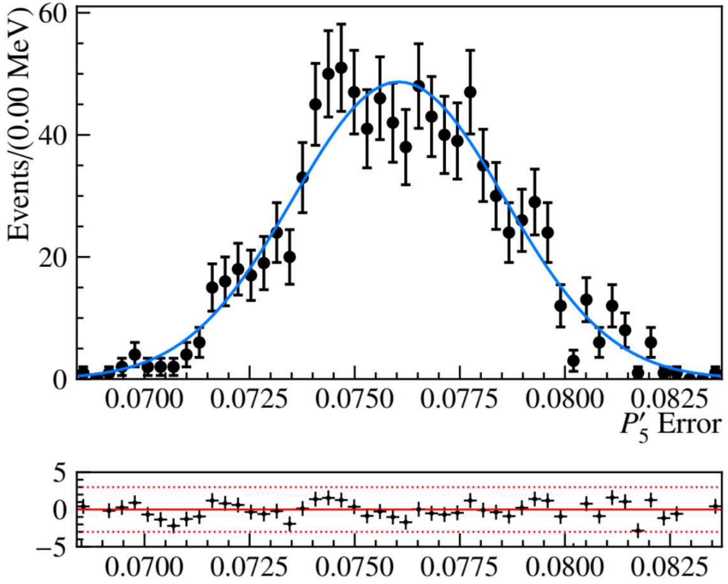

$B^0 \to K^{*0} l^+ l^-$ angular: toy study

Result of toy study

P5' value



P5' error



Extending with a mass shape

```python
# Create mass pdf
mu = zfit.Parameter("mu", 5279, 5200, 5400)
sigma = zfit.Parameter("sigma", 30, 0, 300)
a0 = zfit.Parameter("a0", 1.0, 0, 10)
a1 = zfit.Parameter("a1", 1.0, 0, 10)
n0 = zfit.Parameter("n0", 5, 0, 10)
n1 = zfit.Parameter("n1", 5, 0, 10)

mass = zfit.Space("mass", limits=(4900, 5600))

massPDF = zfit.pdf.DoubleCB(obs=mass, mu=mu, sigma=sigma,
                            alphal=a0, nl=n0, alphar=a1, nr=n1)

pdf = massPDF * angularPDF
```

Build model

$B^0 \to K^{*0}\mu^+\mu^-$ full amplitude

- Measuring the full differential decay ratio [1, 2]
  - Angular, q^2 distribution
  - Branching ratio information

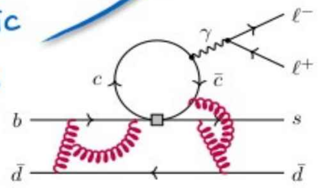
$$\frac{d^4\Gamma}{dq^2\, d\cos\theta_\ell\, d\cos\theta_K\, d\phi} \propto \sum J_i(q^2) f(\cos\theta_\ell, \cos\theta_K, \phi)$$

Form Factors

$$\mathcal{A}_\lambda^{L,R} = \mathcal{N}_\lambda \left\{ \left[(\mathcal{C}_9 \pm \mathcal{C}_9') \mp (\mathcal{C}_{10} \pm \mathcal{C}_{10}') \right] \mathcal{F}_\lambda(q^2) + \frac{2 m_b M_B}{q^2} \left[(\mathcal{C}_7 \pm \mathcal{C}_7') \mathcal{F}_\lambda^T(q^2) - 16\pi^2 \frac{M_B}{m_b} \mathcal{H}_\lambda(q^2) \right] \right\}$$

Wilson coeff.

non-local hadronic matrix elements
"charm-loop"



Fitting libraries and comparison

Python model fitting in HEP

- Scalable: large data, complex models
- Pythonic: use Python ecosystem/language
- Specific HEP functionality:
  - Normalization: specific range, numerical integration,...
  - Composition of models
  - Multiple dimensions
  - Custom models
  - Non-trivial loss (constraints, simultaneous,…)

RooFit

- *Limited customization and extendibility*
- *Sub-optimal scalability for ever larger datasets and modern computing infrastructure*
- Isolated, aging ecosystem, no cutting-edge software
- Not Python native
  - *Memory allocation errors*
  - *Arbitrary C++ limitations*
  - *No real integration into the Python ecosystem*

HEP Python projects

Probfit, TensorProb,…

- Lack generality and extendibility
- “experimental”, but great proof of concept
  - API and Python in general
  - Computational backends (e.g. Cython, TensorFlow)
  - Building an ecosystem (iminuit,…)

General impression in comparison with other HEP packages

Non-HEP

Scipy, lmfit, TensorFlow Probability,...

- Lack of specific HEP features
  - *Normalization: specific range, numerical integration,...*
  - *Composition of models*
  - *Multiple dimensions*
  - *Custom models*
- Irrelevant functionality supported in API
  - Survival function, …

TFA: approach & differences

- Build «optimized» TensorFlow
  - accept-reject as tf.while_loop, Dataset input,...
- ...and hide the tedious, unambiguous parts
  - automatic normalization, Tensor cache, ...
- Well defined structures, e.g.
  - String name order (like columns) in PDFs, data, limits,...
    - pdf(„x“) * pdf(„y“) => pdf(„x“, „y“)
      1-dim 1-dim 2-dim
  - Local/recursive dependency resolution of Parameters

Zfit related packages

phasespace

- Package for phasespace generation of particles
- Covers functionality of TGenPhaseSpace (and more)
- Pure Python (& TensorFlow), integrates seemless with zfit

```
pion = GenParticle('pi+', PION_MASS)
kaon = GenParticle('K+', KAON_MASS)
kstar = GenParticle('K*', KSTARZ_MASS).set_children(pion, kaon)
gamma = GenParticle('gamma', 0)
bz = GenParticle('B0', B0_MASS).set_children(kstar, gamma)

weights, particles = bz.generate(n_events=1000)
```

Zfit: project description

zfit project

- zfit: stable core
  - Unbinned fits, binned WIP
  - n-dim models with integral, pdf, sample
- zfit-physics: HEP specific content
  - BreitWigner, DoubleCB,…
  - Faster development, more content
  - Ideal for contributions
    - Auto testing of new pdfs/func
    - Contribution guidelines

zfit: the project

build stable model fitting ecosystem for HEP

- Integrate into HEP ecosystem

  functionality limited; stable API

- Technical requirements

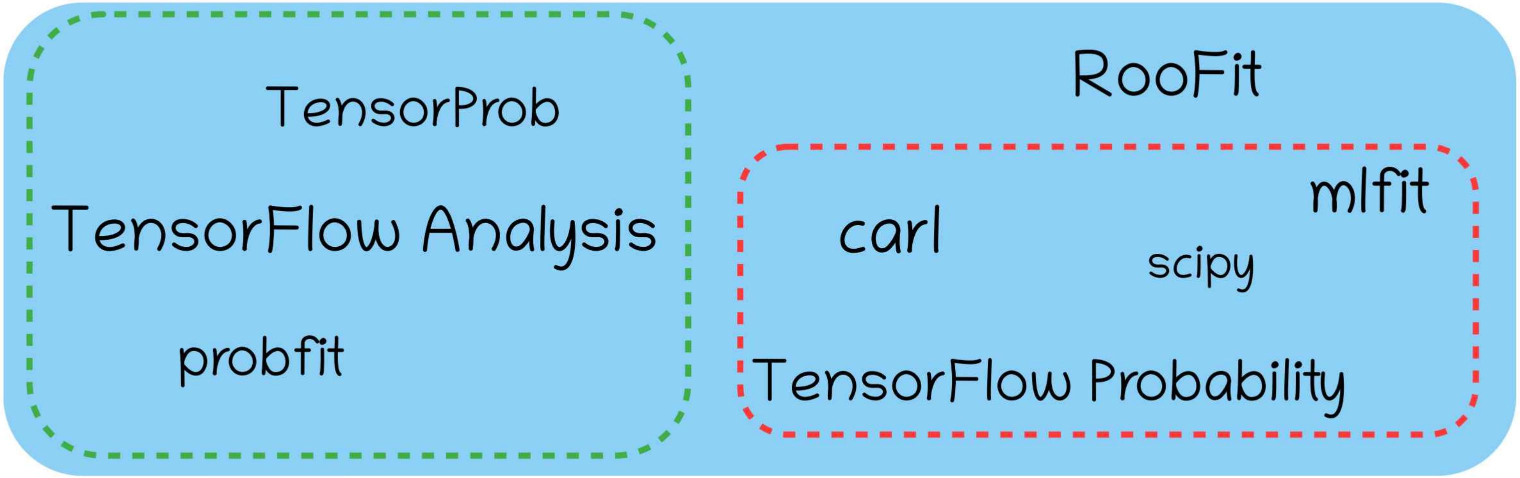
  performance; maintainability

- Analysis requirements

  advanced features; simply extendable code

Fitting in Python

A lot of projects are around

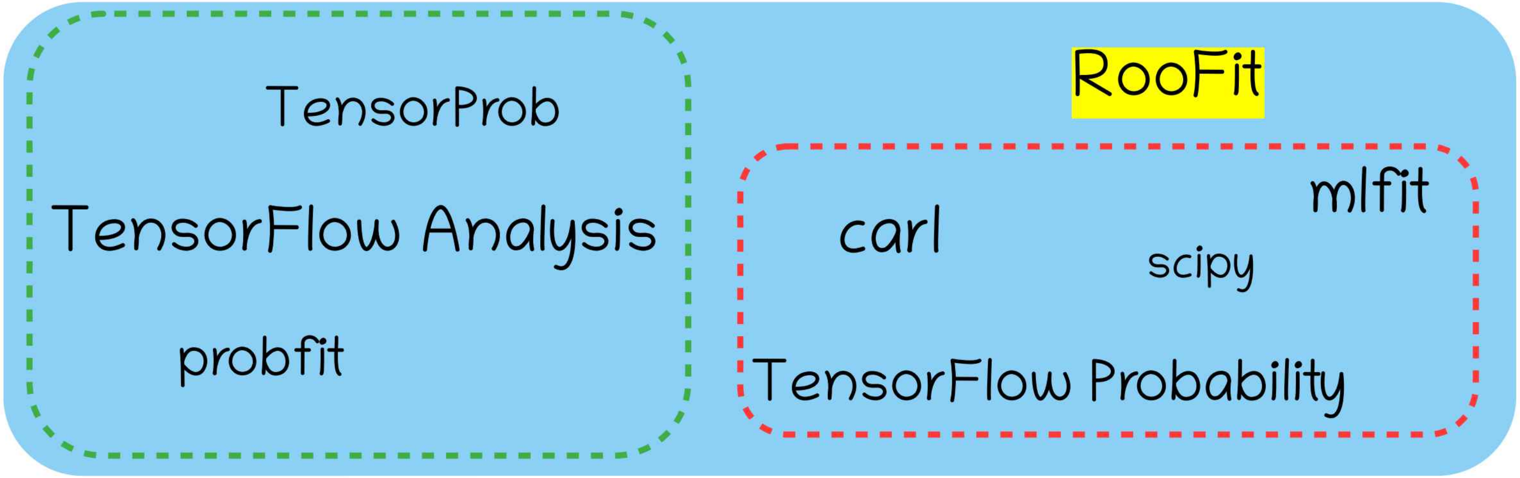


HEP Python

Non-HEP

Fitting in Python

A lot of projects are around

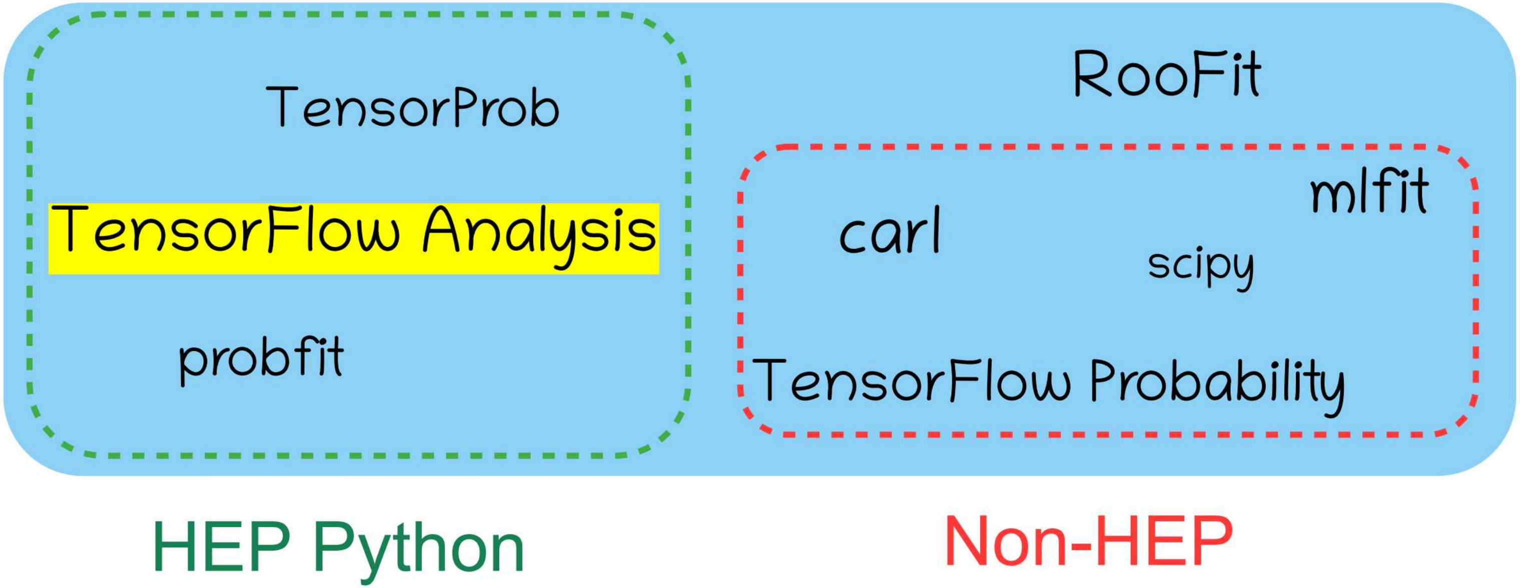


HEP Python

Non-HEP

Fitting in Python

A lot of projects are around



Fitting in Python

A lot of projects are around!

- ~~RooFit~~
- ~~HEP Python fitting projects~~
- ~~Non-HEP~~

Fitting in Python

A lot of projects are around

- ~~RooFit~~
- ~~HEP Python~~
- ~~Non-HEP~~

No optimised model fitting library for HEP that is well integrated into Python

Fitting in Python

A lot of projects are around

- ~~RooFit~~
- ~~HEP Python~~
- ~~Non-HEP~~

No optimised model fitting library for HEP that is well integrated into Python

… but a lot to learn and build from!

zfit

scalable pythonic fitting

zfit: the project

build *the* stable model fitting ecosystem for HEP

...the time has come

zfit: the project

build *the* stable model fitting ecosystem for HEP

- Integrate into HEP ecosystem

  functionality limited; stable API

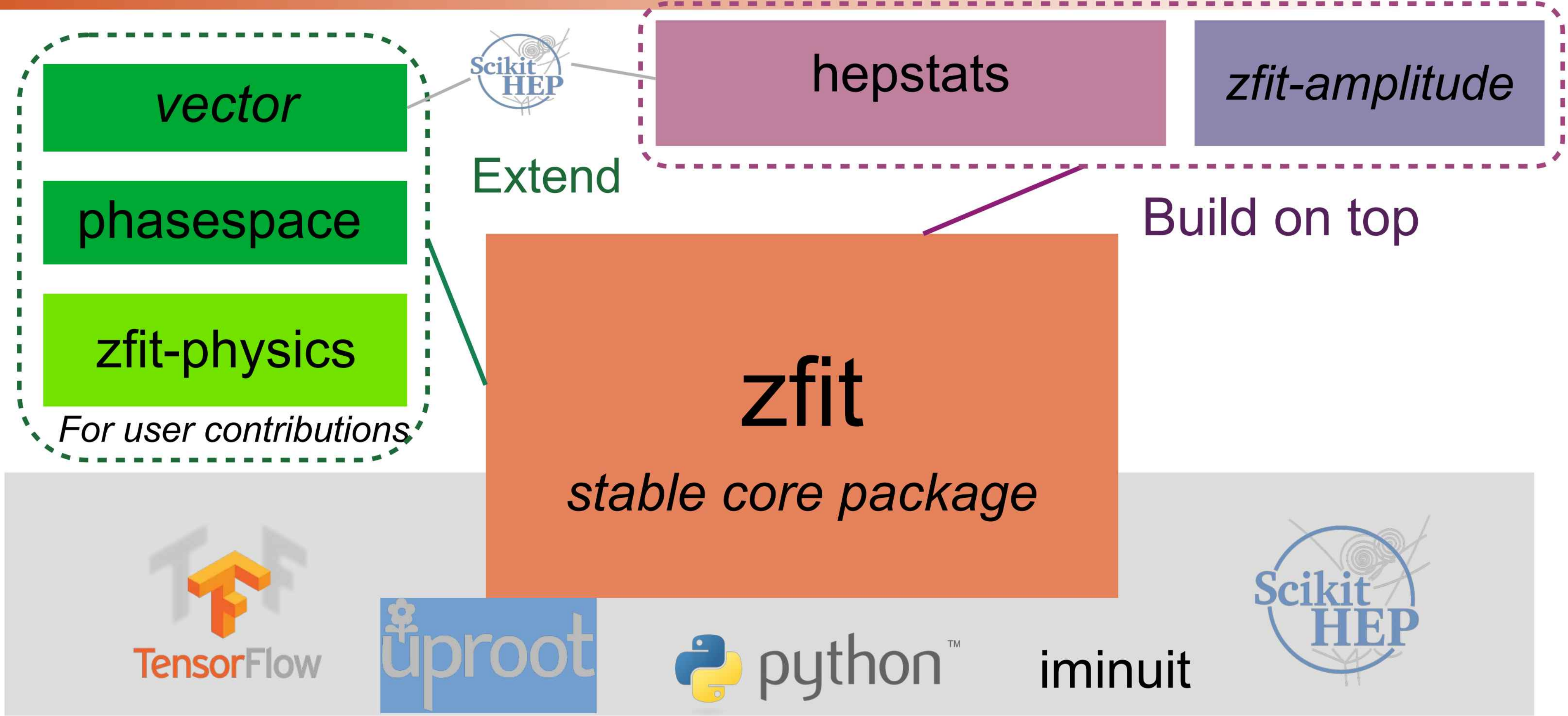
- Technical requirements

  performance; maintainability

- Analysis requirements

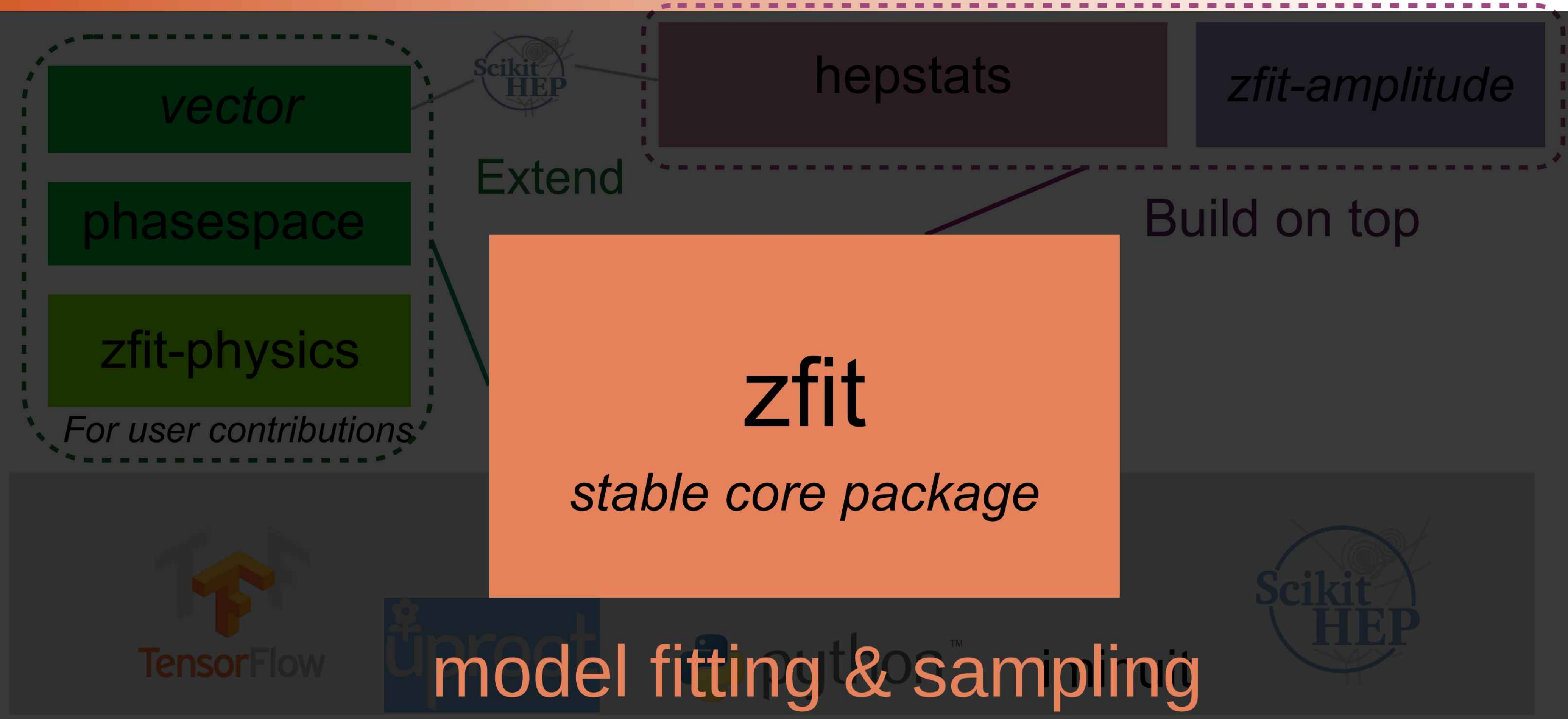
  advanced features; simply extendable code

Ecosystem



vector
phasespace
zfit-physics
For user contributions
Scikit HEP
Extend
hepstats
zfit-amplitude
Build on top
zfit
stable core package
TensorFlow
uproot
python™
iminuit
Scikit HEP

Ecosystem



vector
phasespace
zfit-physics
For user contributions
Extend
hepstats
zfit-amplitude
Build on top
zfit
stable core package
model fitting & sampling
TensorFlow
uproot
python
iminuit
Scikit HEP

Ecosystem: API & Workflow

Establish a stable API

- High level libraries (statistics, plotting,...)
  - „code against an interface, not an implementation“
- Replace each component
  - Allow other libraries to implement custom parts

Many discussions with community
to avoid splitting/duplication

Pythonic

- Pure Python («pip install zfit»)
- Integrated into python ecosystem
    - Load ROOT files (uproot,no ROOT dependence!)
    - Use Minuit for minimization (iminuit)
    - Data preprocessing with Pandas DataFrame
    - Plotting with matplotlib
    - High level statistics (lauztat, more WIP)
- Extendable classes
    - e.g. custom PDF

Scalable

- TensorFlow **hidden** backend, uses graphs
  - numpy-like syntax
  - parallelization on CPU/GPU, analytic gradient,...
- Writing functions simple for users *and* developers
  - No Cython, MPI, CUDA,... for *state-of-the-art performance*
  - No low-level maintenance required!
- Used in multiple physics libraries and analyses

Scalable: TensorFlow

- Deep Learning framework by Google
- Modern, declarative graph approach
- Built for highly parallelized, fast communicating CPU, GPU, TPU,… clusters
- Built to use «Big Data»

Zfit library examples

Minimize Python function

```python
def func(x):
    x = np.array(x)  # make sure it's an array
    return np.sum((x - 0.1) ** 2 + x[1] ** 4)

func.errordef = 0.5

params = [1, -3, 2, 1.4, 11]

result = minimizer.minimize(func, params)
```

Model, loss building

sum of two pdfs

```
sum_pdf = zfit.pdf.SumPDF([gauss, exponential], fracs=frac)
```

shared parameters

```
mu_shared = zfit.Parameter("mu_shared", 1., -4, 6)

gauss1 = zfit.pdf.Gauss(mu=mu_shared, sigma=sigma1, obs=obs)
gauss2 = zfit.pdf.Gauss(mu=mu_shared, sigma=sigma2, obs=obs)
```

simultaneous loss

```
nll1 = zfit.loss.UnbinnedNLL(model=gauss1, data=data1)
nll2 = zfit.loss.UnbinnedNLL(model=gauss2, data=data2)
nll_simultaneous2 = nll1 + nll2
```

From classical

to more TensorFlow

Model, loss building

Simple combinations

```
func_n = zfit.func.ZFunc(...)  # pseudo code
func = func_1 + func_2 * func_3
```

Composite Parameter

```
pdf = zfit.pdf.Gauss(mu=tensor1, sigma=4)
```

Custom Loss

```
loss = zfit.loss.SimpleLoss(lambda: tensor_loss)
```

up to pure TensorFlow

=> use all of zfit functionality like minimizers

Model building

```
obs = zfit.Space("x", limits=(-10, 10))

mu =    zfit.Parameter("mu",          1,  -4,  6)
sigma = zfit.Parameter("sigma",       1, 0.1, 10)
lambd = zfit.Parameter("lambda",     -1,  -5,  0)
frac =  zfit.Parameter("fraction", 0.5,   0,  1)

gauss = zfit.pdf.Gauss(mu=mu, sigma=sigma, obs=obs)
exponential = zfit.pdf.Exponential(lambd, obs=obs)
```

parameters

models

Simultaneous fit

```python
mu_shared = zfit.Parameter("mu_shared", 1., -4, 6)
sigma1 = zfit.Parameter("sigma_one", 1., 0.1, 10)
sigma2 = zfit.Parameter("sigma_two", 1., 0.1, 10)

gauss1 = zfit.pdf.Gauss(mu=mu_shared, sigma=sigma1, obs=obs)
gauss2 = zfit.pdf.Gauss(mu=mu_shared, sigma=sigma2, obs=obs)
```

shared parameters

```python
nll_simultaneous = zfit.loss.UnbinnedNLL(model=[gauss1, gauss2],
                                         data=[data1, data2])

nll1 = zfit.loss.UnbinnedNLL(model=gauss1, data=data1)
nll2 = zfit.loss.UnbinnedNLL(model=gauss2, data=data2)
nll_simultaneous2 = nll1 + nll2
```

Completely equivalent