BAT.jl - Upgrading the Bayesian Analysis Toolkit

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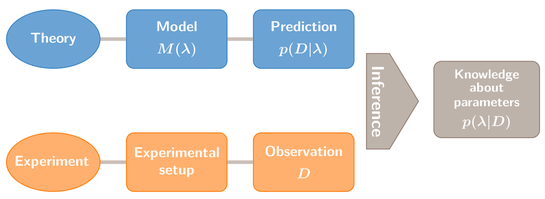
1. The Motivation

Statistical inference

goal: gain knowledge about model from data

typical analysis tasks:

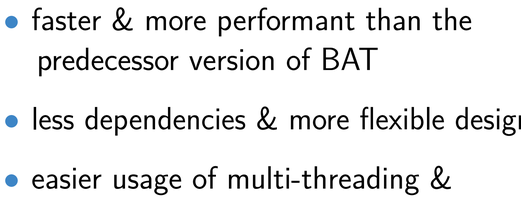
- estimation of model parameters
- model comparisons
- hypothesis testing
- limit setting
- goodness-of-fit tests



3. The Curse

Computation of posterior

- challenging task for real-world problems
  → curse of dimensionality



advanced algorithms are needed to perform high-dimensional:

- sampling of posterior
- optimization
- integration
- marginalization

5. The Rewrite

NEW

BAT.jl

- rewrite of BAT from scratch in the Julia programming language

design goals:

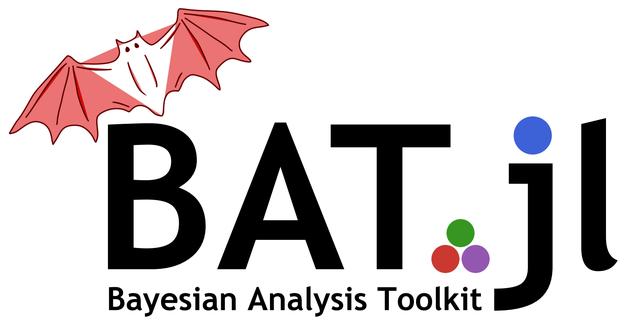
- faster & more performant than the predecessor version of BAT
- less dependencies & more flexible design
- easier usage of multi-threading & distributed computing
- open for further fields of research (become independent of ROOT)

→ new code structure & new algorithms

7. The Features

Current features of BAT.jl

- registered Julia package (v. 0.5)
- user-definable likelihoods & priors
- Metropolis-Hastings sampling algorithm
- native parallel running of Markov chains
- integrals with Adaptive Harmonic Mean Integration [1808.08051]
- call of likelihoods from other languages (directly or via binary RPC calls)
- formatted output & plotting recipes



github.com/bat/bat.jl

The How-To

Installation

install & setup BAT via Julia's built-in package manager

```
# installation via package manager (only first use)
using Pkg
pkg"add BAT"

# activate BAT
using BAT
```

Define model

define the statistical model in terms of the log-likelihood

- ✚ implement custom likelihoods
- ✚ use common distributions from *Distributions.jl*
- ✚ call code in python, C/C++, Fortran, R, mathematica, ... via Julia's interfaces
- ✚ call external likelihoods in any language via BAT.jl's RPC

```
log_likelihood = let μ = [15, 10], σ = [1.5, 2.5]
    params -> begin
        # custom implementation of normal distribution
        normal = ( -0.5 * log(2π*σ[1]^2)
                   -(params.λ1-μ[1])^2 / (2σ[1]^2) )

        # normal distribution from Distributions.jl
        n1 = pdf(Normal(μ[2]-5, σ[2]), params.λ2)
        n2 = pdf(Normal(μ[2]+5, σ[2]), params.λ2)

        return normal + log(n1 + 3*n2)
    end
end
```

Define prior

- ✚ implement custom priors
- ✚ use common distributions from *Distributions.jl*
- ✚ use histograms as priors

```
prior = NamedTupleDist(
    λ1 = Normal(6, 2.5), #for parameter1
    λ2 = -30.0..30.0     #for parameter2
)
```

Define prosterior

```
posterior = PosteriorDensity(log_likelihood, prior)
```

Setup sampler

choose sampling algorithm, number of chains & number of samples

- ✚ possible to adjust sampler settings for: proposal distribution, MCMC tuning algorithm, convergence test, chain initialization, tuning/burn-in strategy

```
# choose sampling algorithm
algorithm = MetropolisHastings()

nchains = 8       # number of Markov chains
nsamples = 10^6   # number of samples per chain
```

Generate samples

```
samples = bat_sample(
    posterior, (nsamples, nchains), algorithm
)
```

parameters	log_posterior	log_prior	weight
(λ1 = 11.063, λ2 = 17.904)	-14.160	-7.980	2
(λ1 = 11.113, λ2 = 18.104)	-14.209	-8.021	4
⋮	⋮	⋮	⋮

Show sample statistics

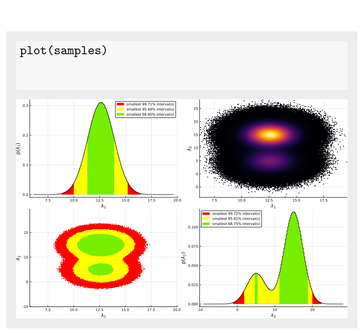
```
stats = bat_stats(samples)
```

```
Mode: [12.617, 15.000]    Mean: [12.618, 12.492]
Covariance: [1.650 -0.015; -0.015 25.063]
```

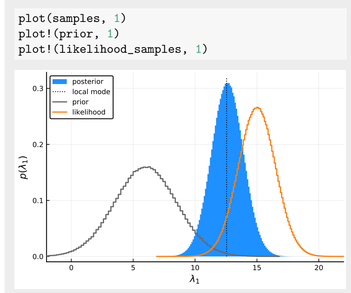
Visualize results

- ✚ predefined & customizable plot recipes
- ✚ individual plotting

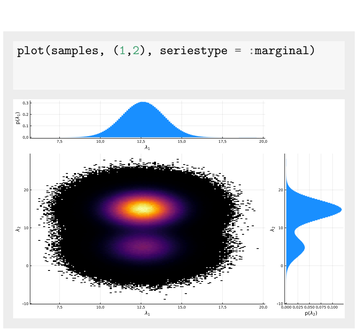
```
plot(samples)
```



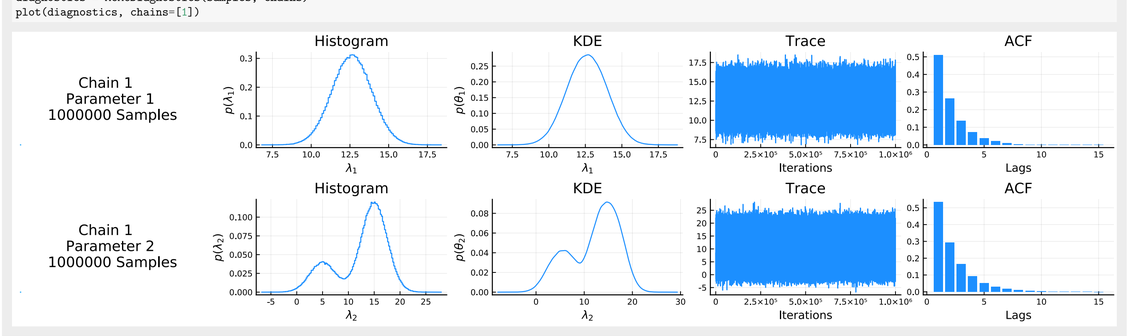
```
plot(samples, 1)
plot!(prior, 1)
plot!(likelihood_samples, 1)
```




```
plot(samples, (1,2), seriestype = :marginal)
```



```
diagnostics = MCMCDiagnostics(samples, chains)
plot(diagnostics, chains=[1])
```



Calculate integral from samples

- ✚ Adaptive Harmonic Mean Integration (AHMI)

```
evidence = bat_integrate(samples)
```

```
evidence: 7.8e-5 ± 2.1e-7
```

Export samples to file

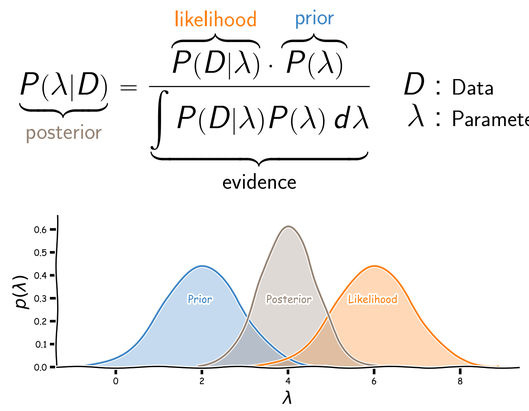
```
bat_write("samples.hdf5", samples)
```

2. The Theory

Bayesian inference

- use Bayes' theorem to update knowledge about model parameters λ from data D
- Bayes' theorem:

$$\underbrace{P(\lambda|D)}_{\text{posterior}} = \frac{\overbrace{P(D|\lambda)}^{\text{likelihood}} \cdot \overbrace{P(\lambda)}^{\text{prior}}}{\underbrace{\int P(D|\lambda)P(\lambda)\,d\lambda}_{\text{evidence}}} \qquad \begin{matrix} D: \text{Data} \\ \lambda: \text{Parameters} \end{matrix}$$



- posterior contains the knowledge about the parameters for given data

4. The Tool

Bayesian Analysis Toolkit - BAT

Comput. Phys. Commun. 180 (2009) 2197

- collection of algorithms & methods for Bayesian inference
- user-defined statistical models in a multi-purpose language (no tool-specific modeling language)
- use of Markov chain Monte Carlo algorithms for sampling of posterior
- toolbox-character: choose from different methods to solve custom problems
- first version released in 2008 (written in C++, depending on ROOT)

6. The Language

The Julia language

- modern general-purpose language (v. 1.0 released 2018)
- focus on high-performance numerical & scientific computing
- built-in package-management system
- large scientific community & growing ecosystem (> 3000 registered packages)
- features: multiple dispatch, dynamic typing, meta-programming & macros, ...
- natively possible to call code in other languages, e.g. python, C, Fortran, ...

8. The Future Prospects

Further development of BAT.jl

- release of v. 1.0 planned for this month
- finalizing main features & API design
- new sampling algorithms (WIP)
- support for distributed computing (WIP)
- development of examples, tutorials & templates for common analysis tasks (WIP)
- much more to come...
  → stay tuned!