

# The Bayesian Analysis Toolkit (BAT)

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on behalf of the BAT team



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9th, 2020

# Introduction

- ▶ The Bayesian Analysis Toolkit (BAT):  
A software package for Bayesian inference
  - ▶ Typical tasks: Given a set of data and prior knowledge
    - ▶ estimate parameters
    - ▶ compare models (Bayes factors)
- according to Bayes theorem

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- ▶ Functionalities
  - ▶ Posterior space exploration via  
Markov chain Monte-Carlo (MCMC)
  - ▶ Integration of non-normalized posterior  
(i.e. evidence calculation)
  - ▶ User-friendly plotting and reporting

# Development History

- ▶ Original: BAT-C++ v1.0
- ▶ Very successful over the years, > 250 citations (INSPIRE)

[Caldwell et al., DOI: 10.1016/j.cpc.2009.06.026 (2009).]

- ▶ Written in C++, based on CERN ROOT
- ▶ Proven in many real-life use cases
- ▶ Wide user base, esp. in high-energy, nuclear and astro-physics

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  - ▶ Proven in many real-life use cases
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- ▶ By now reached flexibility limit of original software design
- ▶ Started complete re-design in 2017

# Design goals for new version of BAT

- ▶ Core philosophy: User provides likelihood (typically expensive, high data volumes, etc.)  
BAT does the rest
- ▶ Easy to use with defaults, but allow for detailed fine-tuning
- ▶ Multiple MCMC algorithms (BAT-C++ only supports Metropolis-Hastings)
- ▶ Deep support for parallel operation:
  - ▶ Parallelize both likelihood and MCMC chains
  - ▶ Local (multiple threads) plus distributed (compute clusters)
- ▶ Auto-differentiation for mode-finding, HMC, etc.
- ▶ Choice of programming language?

# Choice of Programming Language

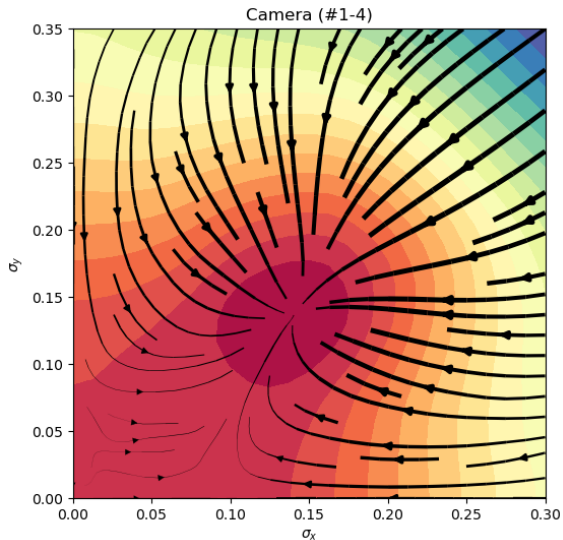
- ▶ New version: BAT.jl, written in Julia
- ▶ C++: Complex, takes long to learn, multi-platform tricky, interactive use requires ROOT/Cling
- ▶ Python: Hard to write high-performance likelihoods without falling back to C/C++

# Choice of Programming Language

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- ▶ C++: Complex, takes long to learn, multi-platform tricky, interactive use requires ROOT/Cling
- ▶ Python: Hard to write high-performance likelihoods without falling back to C/C++
- ▶ Julia provides:
  - ▶ C/C++ performance with Python-like simplicity
  - ▶ excellent multi-threading
  - ▶ native cluster-computing
  - ▶ excellent auto-differentiation
  - ▶ native GPU computing
  - ▶ ability to easily call C, Fortran, C++, Python, R, ...
  - ▶ superior code composability due to multiple dispatch



# Autodifferentiation in Julia



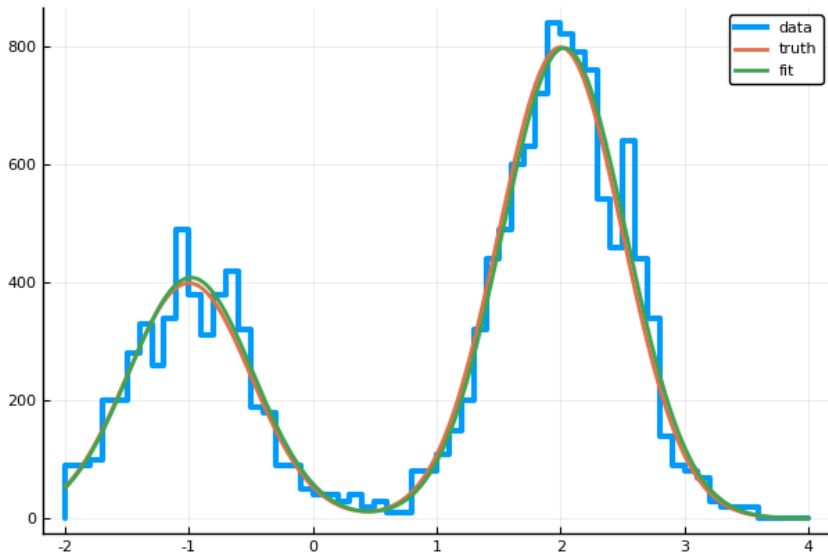
Julia powerful enough to allow for AD of (almost arbitrary code).

# BAT.jl

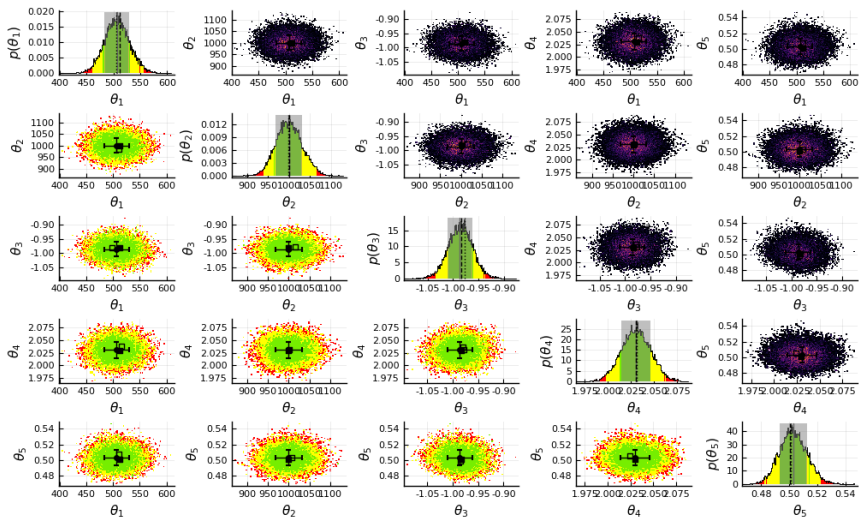
- ▶ MCMC with Metropolis-Hastings (like BAT-C++), also HMC (Stan-like) now
- ▶ New ARP sample weighting scheme
- ▶ New posterior integration algorithm AHMI
- ▶ Release of v1.2 imminent
- ▶ <https://github.com/BAT/BAT.jl>



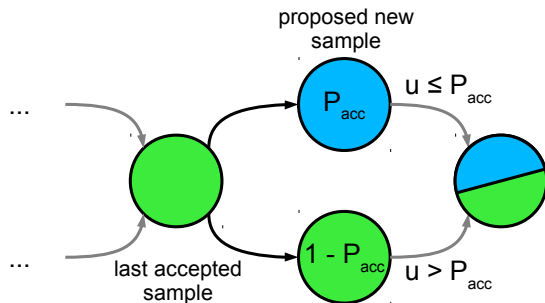
# Simple BAT.jl example: Fit Histogram



# BAT.jl plotting: Posterior projections



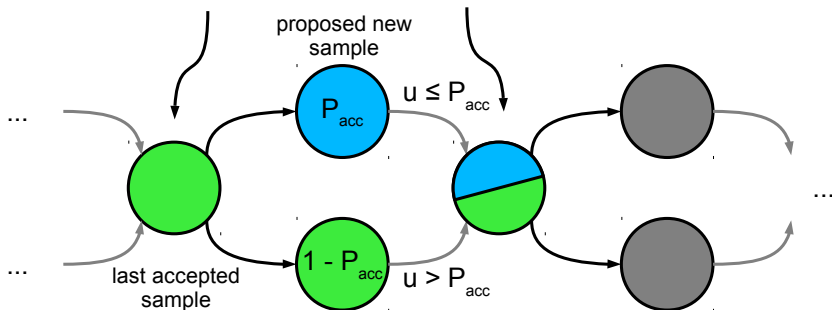
# Accept/Reject Probability (ARP) Weights



- ▶ Schrödinger's cat for samples

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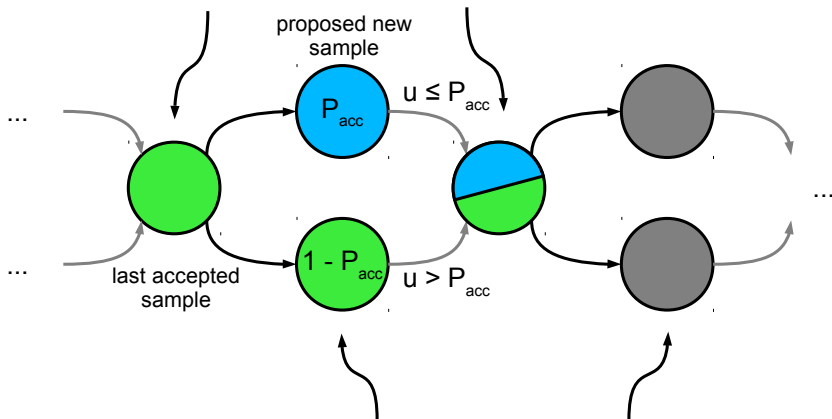
## Standard Metropolis MCMC States



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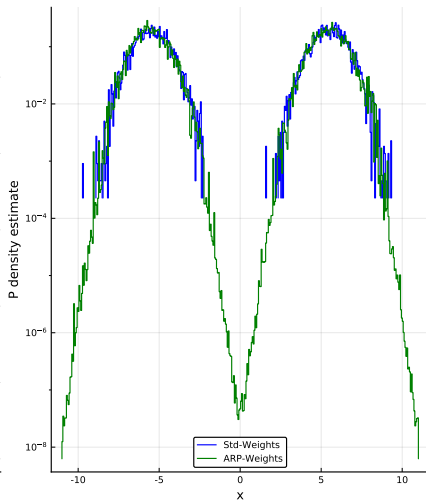
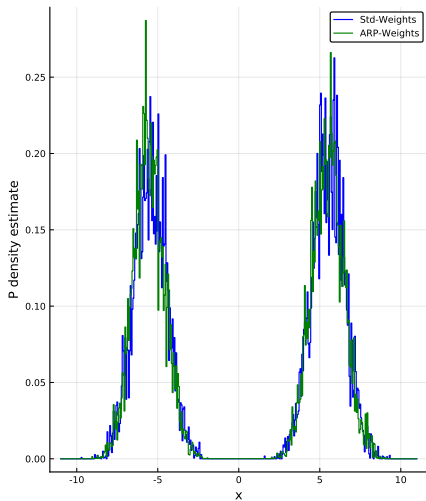
Standard Metropolis MCMC States



ARP-Weights MCMC States

- ▶ Schrödinger's cat for samples

# ARP Sample Weights



- ▶ New sample weighting scheme keeps rejected samples, allows insight in low-probability posterior areas



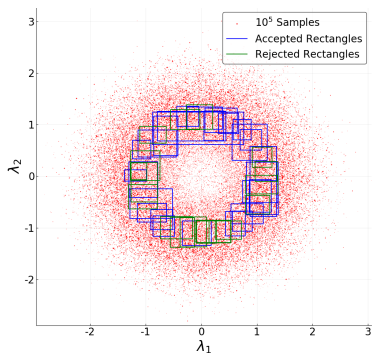
# Adaptive Harmonic Mean Integration

- ▶ Given  $N$  samples  $\Lambda_i$  drawn from posterior, can estimate integral via harmonic mean:

$$\hat{I} \equiv \frac{NV}{\sum_{i=1}^N \frac{1}{f(\Lambda_i)}} .$$

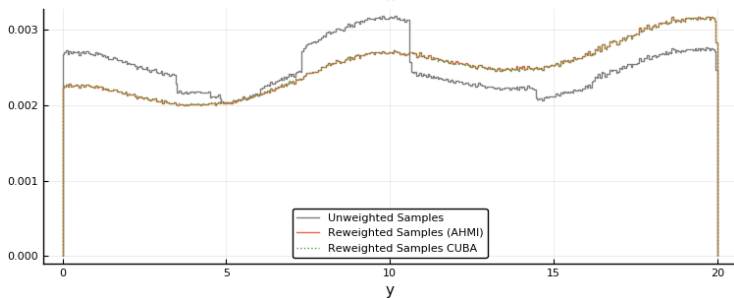
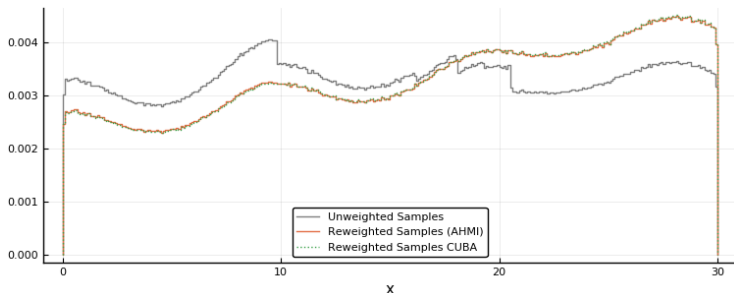
- ▶ Problem: variance of estimator diverges in the general case
- ▶ AHMI algorithm:
  - ▶ Whiten sample distribution
  - ▶ Generate set of hyper-rectangles with bounded variance
  - ▶ Compute individual harmonic mean integrals
  - ▶ Estimate correlation of integrals
  - ▶ Combine integrals into robust overall integral with error estimate

# Adaptive Harmonic Mean Integration (AHMI)



- ▶ Computes posterior integral/evidence from samples via harmonic mean [arXiv:1808.08051 (2018)]
- ▶ Operates in hyper-rectangles with limited posterior variance to control integral variance

# Space partitioning AHMI reweighting



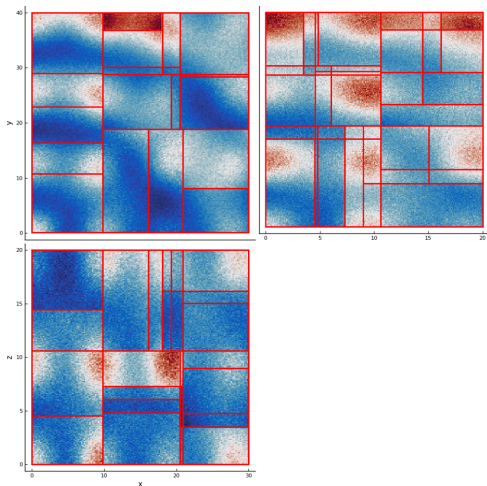
# Parameter space partitioning (Experimental)

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- ▶ Parallelization potential of likelihood often limited
- ▶ Increasing number of chains doesn't help (burn-in cost)

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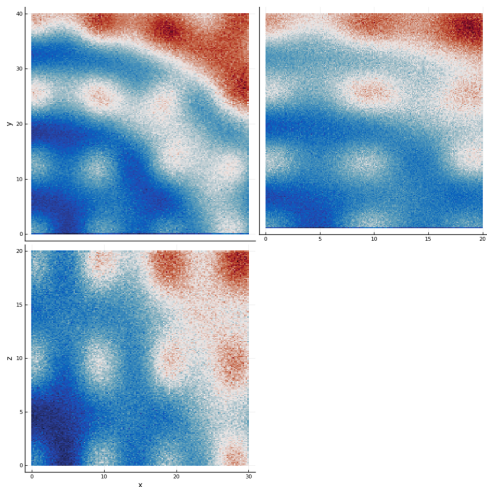
- ▶ MCMC expensive, need maximum parallelization
- ▶ Parallelization potential of likelihood often limited
- ▶ Increasing number of chains doesn't help (burn-in cost)
- ▶ New concept: partition parameter space  
run separate set of chains in each subspace
- ▶ Rationale: posterior in small subspaces simpler,  
fast burn-in
- ▶ Challenge: find good partitioning for given posterior,  
work in progress

# Parameter Space Partitioning, Raw



- ▶ Subspaces contains unequal probability mass:  
can't just stitch MCMC results together

# Parameter Space Partitioning, Reweight



- ▶ Solution: Use AHMI to integrate posterior in each subspace, then reweight by integral

# Conclusions and Outlook

- ▶ BAT concept:  
user brings domain knowledge and likelihood,  
BAT provides robust sampling, integration and visualization
- ▶ Current BAT (C++) is a success story,  
but flexibility limit reached
- ▶ Release of BAT.jl (Julia) v2.0 imminent,  
focus on ease of use, parallelization and modern algorithms
- ▶ Future improvements: Lot's of ideas, but will strive for  
quality, not quantity (of algorithms, etc.), ...



# Appendix