

Turing.jl: what's new?

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What is Turing.jl?

Turing.jl is a package that makes Bayesian statistical inference easy. The user writes a statistical model using simple, intuitive syntax, and gives it observed data. With a single function call they can access a variety of inference methods, such as Markov chain Monte Carlo sampling from the posterior distribution.

```
using Turing, StatsPlots

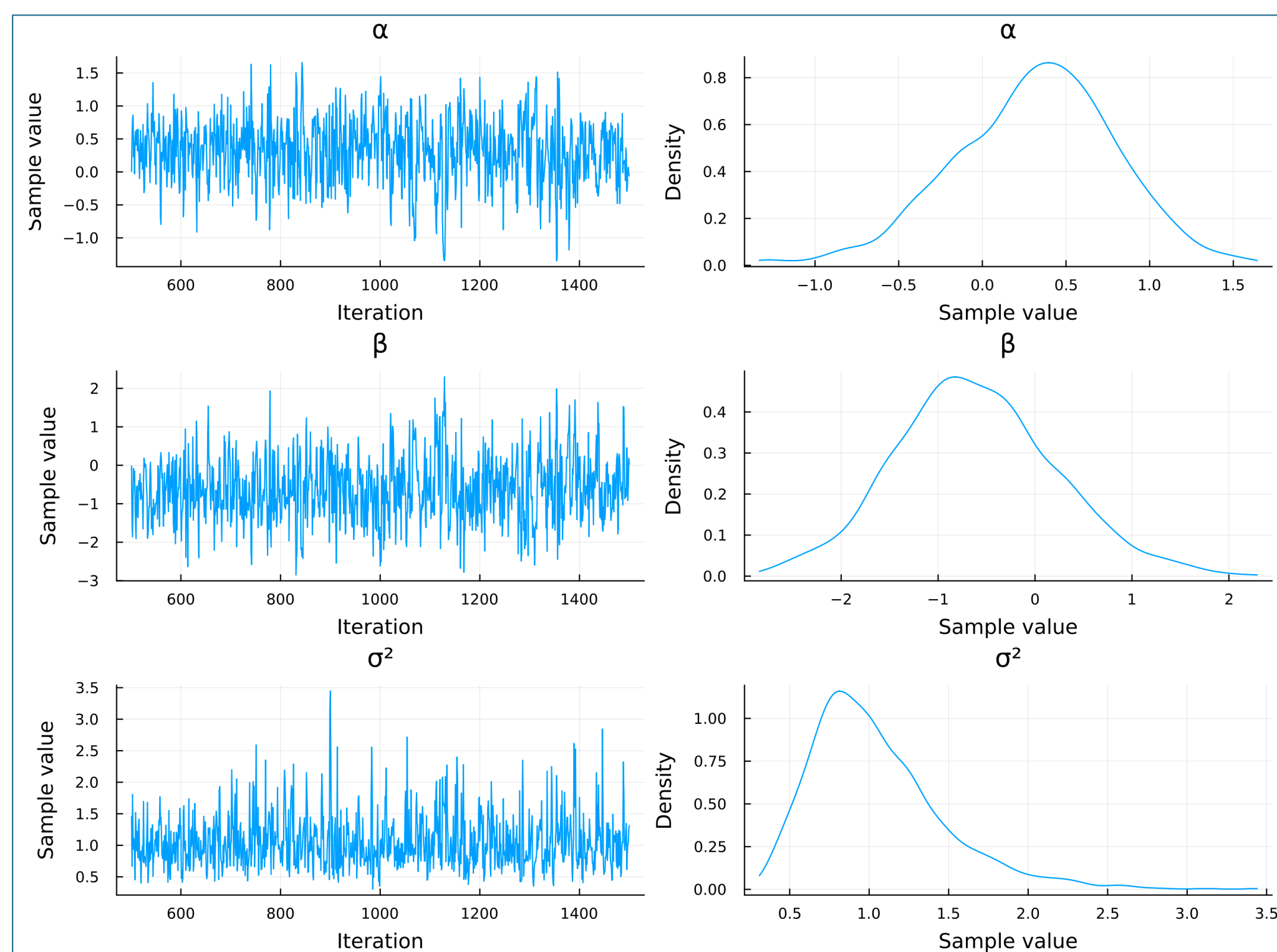
@model function linear_regression(x)
  # Priors
  α ~ Normal(0, 1)
  β ~ Normal(0, 1)
  σ² ~ truncated(Normal(0, 1), lower=0)

  # Likelihood
  μ = α .+ β .* x
  y ~ MvNormal(μ, σ² * I)
end

x = rand(10)
y = 0.4 .* x .- 0.4 .+ randn(10)

m = linear_regression(x)
m_conditioned = m | (; y=y)

chain = sample(m_conditioned, NUTS(), 1000)
plot(chain)
```



> 9 years of development
> 2000 GitHub stars
> 500 citations

Applications

- Astrophysics, drug research, COVID modelling, cosmology, etc.
- Industry, academia, and public sector.

Turing models can have

- Continuous and discrete parameters
- Custom distributions
- Normal Julia control flow (if, for, while, etc.), including stochastic control flow
- Submodels within models
- Calls to (almost) any external libraries

Inference methods

- Markov chain Monte Carlo (Hamiltonian, particle methods, Gibbs sampling, etc.)
- External samplers
- Variational inference
- Maximum likelihood & maximum a posteriori

Works with

- DifferentialEquations.jl
- ForwardDiff, ReverseDiff, Enzyme & Mooncake
- Pigeons.jl
- Pathfinder.jl
- Lux.jl
- HiddenMarkovModels.jl
- Gaussian processes

Our development priorities

Pay off technical debt,
simplify internals

Improve
documentation

Fix a stable
v1.0 interface



turinglang.org



Code examples



GitHub

In progress

v1.0 release

A stable user-facing interface: @model syntax, submodels, analysing chains.

Automatic differentiation

More extensive testing against, and support for, the next-generation autodiff packages Mooncake and Enzyme.

A new MCMC chain type

Faster; better support for heterogeneous data; a more coherent interface.

Variational inference improvements

- Data point subsampling (i.e. doubly stochastic variational inference).
- More modular and easily extendable to the benefit of algorithm developers and researchers.

And more ...

- Simpler evaluation contexts and tilde-pipeline
- Better data structures for model traces
- Interoperability with JuliaBUGS.jl

Done

Submodels

Allow you to use one Turing.jl model within another.

- New syntax: $x \sim \text{to_submodel}(m)$ instead of $\text{@submodel}(m)$
- Variables in submodels can now be conditioned or fixed to given values.

Table comparing automatic differentiation backends

| Model name \ AD type | EnzymeForward | EnzymeReverse | FiniteDifferences | ForwardDiff | MooncakeForward | MooncakeReverse | ReverseDiff | ReverseDiffCompiled | Zygote |
|-------------------------------|---------------|---------------|-------------------|-------------|-----------------|-----------------|-------------|---------------------|----------|
| broadcast_macro | 3.016 | 2.826 | 35.892 | 1.434 | 25.138 | 6.426 | 29.891 | 2.907 | error |
| dot_assume | 2.916 | 1.902 | 76.795 | 1.426 | 29.447 | 5.064 | 20.883 | 1.882 | error |
| dot_observe | 2.972 | 2.648 | 27.654 | 1.686 | 19.247 | 7.219 | 56.512 | 5.333 | error |
| dynamic_constraint | 2.733 | 2.432 | 35.363 | 1.343 | 26.817 | 6.227 | 32.890 | 2.648 | 1735.748 |
| multiple_constraints_same_var | 3.056 | 2.227 | 59.541 | 1.299 | 27.281 | 12.725 | 29.531 | 2.343 | error |
| observe_index | 2.964 | 2.684 | 27.803 | 1.484 | 17.022 | 6.959 | 56.474 | 5.235 | error |
| observe_literal | 2.954 | 2.466 | 28.934 | 1.454 | 18.641 | 6.989 | 35.872 | 3.735 | 2922.312 |
| observe_multivariate | 4.063 | 2.600 | 52.210 | 1.338 | 22.467 | 5.379 | 24.795 | 2.238 | error |
| observe_submodel | 2.553 | 2.152 | 25.499 | 1.400 | 13.016 | 5.464 | 26.133 | 2.398 | 3253.258 |

turinglang.org/ADTests

Particle methods overhaul

Sequential Monte Carlo and Particle Gibbs samplers are now approximately 50–400% faster.

Variational inference improvements

- Full-rank Gaussian variational approximations, not just mean-field approximations
- Parameter-free stochastic optimization algorithms.

And more ...

- More granular selection of variables for the Gibbs sampler
- Mode estimation improvements
- Log probabilities now in chains
- Parallel progress bars!

Future plans

New syntax for declaring variables

Would allow users to list names, types, and dimensions of all variables in a model. This would simplify Turing internals, make nonparametric methods more reliable to implement, and make it easier to implement robust samplers.

Submodels

Make submodels more first-class citizens, interchangeable with distributions.

Full thread-safety

Within a Turing.jl model, currently one can parallelise observations, but not creating parameters. We would like to lift this limitation.

And more ...

- brms-like interface for generalised linear models
- Educational materials on Bayesian inference
- GPU support