

greta

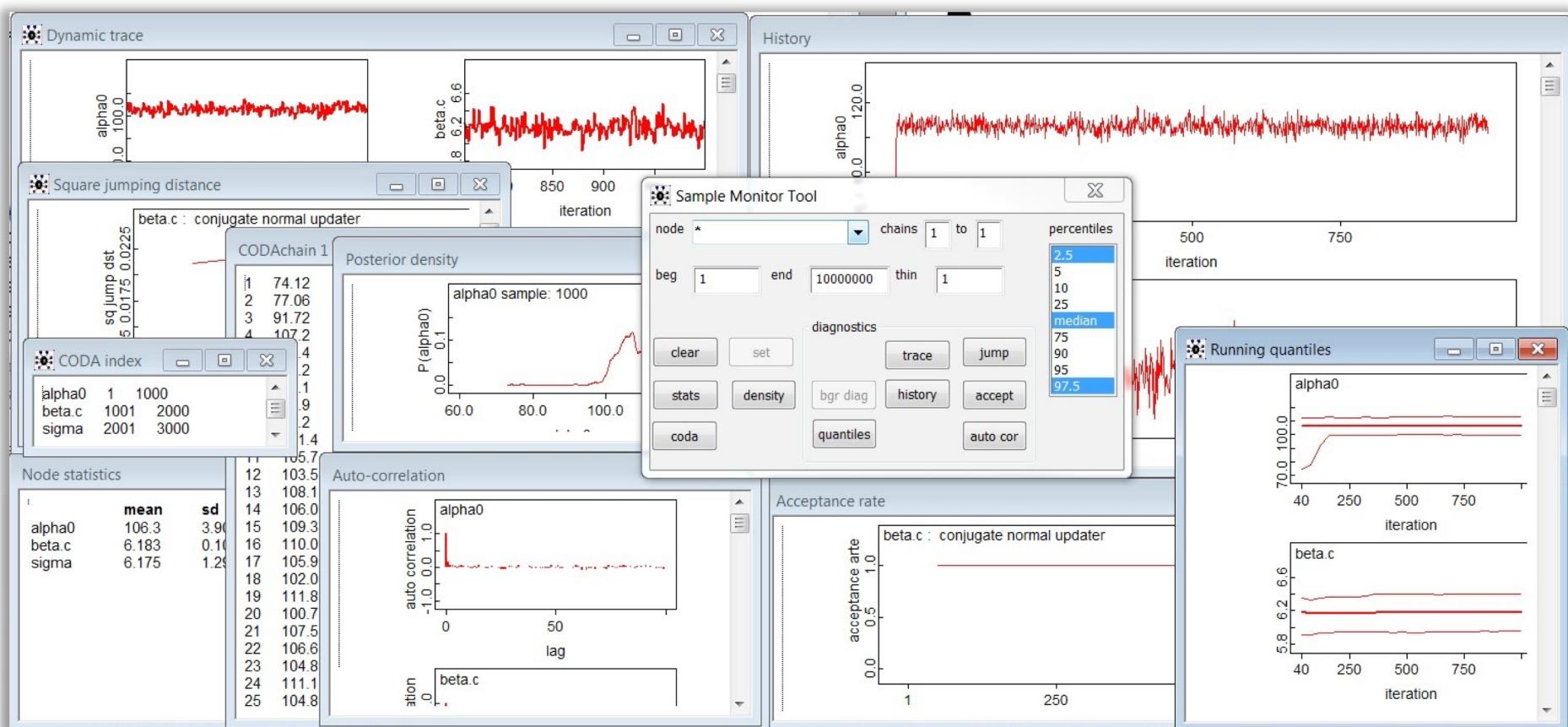


simple and scalable statistical modelling in R

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greta-dev.github.io/greta

BUGS



BUGS

Bugs language model

```
model{
  for(i in 1 : N){
    for(j in 1 : T){
      Y[i , j] ~ dnorm(mu[i , j], tau.c)
      mu[i , j] <- alpha[i] + beta[i] * (x[j] - xbar)
    }
    alpha[i] ~ dnorm(alpha.c, alpha.tau)
    beta[i] ~ dnorm(beta.c, beta.tau)
  }
  alpha.c ~ dnorm(0.0, 1.0E-6)
  alpha.tau ~ dgamma(0.001, 0.001)
  beta.c ~ dnorm(0.0, 1.0E-6)
  beta.tau ~ dgamma(0.001, 0.001)
  tau.c ~ dgamma(0.001, 0.001)
  alpha0 <- alpha.c - beta.c * xbar
  sigma <- 1 / sqrt(tau.c)
}
```

Dynamic trace

Square jumping distance

CODA index

	mean	sd
alpha0	106.3	3.90
beta.c	6.183	0.10
sigma	6.175	1.29

Node statistics

iteration

iteration

Stan



Stan

```
data {
    int<lower=0> N;      // number of data items
    int<lower=0> K;      // number of predictors
    matrix[N, K] x;      // predictor matrix
    vector[N] y;         // outcome vector
}
transformed data {
    matrix[N, K] Q_ast;
    matrix[K, K] R_ast;
    matrix[K, K] R_ast_inverse;
    // thin and scale the QR decomposition
    Q_ast = qr_Q(x)[, 1:K] * sqrt(N - 1);
    R_ast = qr_R(x)[1:K, ] / sqrt(N - 1);
    R_ast_inverse = inverse(R_ast);
}
parameters {
    real alpha;           // intercept
    vector[K] theta;      // coefficients on Q_ast
    real<lower=0> sigma; // error scale
}
model {
    y ~ normal(Q_ast * theta + alpha, sigma); // likelihood
}
generated quantities {
    vector[K] beta;
    beta = R_ast_inverse * theta; // coefficients on x
}
```

Stan

```
data {  
    real alpha;  
    real beta;  
    real<lower=0> sigma2;  
    int<lower=0> J;  
    int y[J];  
    vector[J] z;  
    int n[J];  
}  
  
transformed data {  
    real<lower=0> sigma;  
    sigma <- sqrt(sigma2);  
}  
  
parameters {  
    real theta1;  
    real theta2;  
    vector[J] X;  
}  
  
model {  
    real p[J];  
    theta1 ~ normal(0, 32); // 32^2 = 1024  
    theta2 ~ normal(0, 32);  
    X ~ normal(alpha + beta * z, sigma);  
    y ~ binomial_logit(n, theta1 + theta2 * X);  
}
```

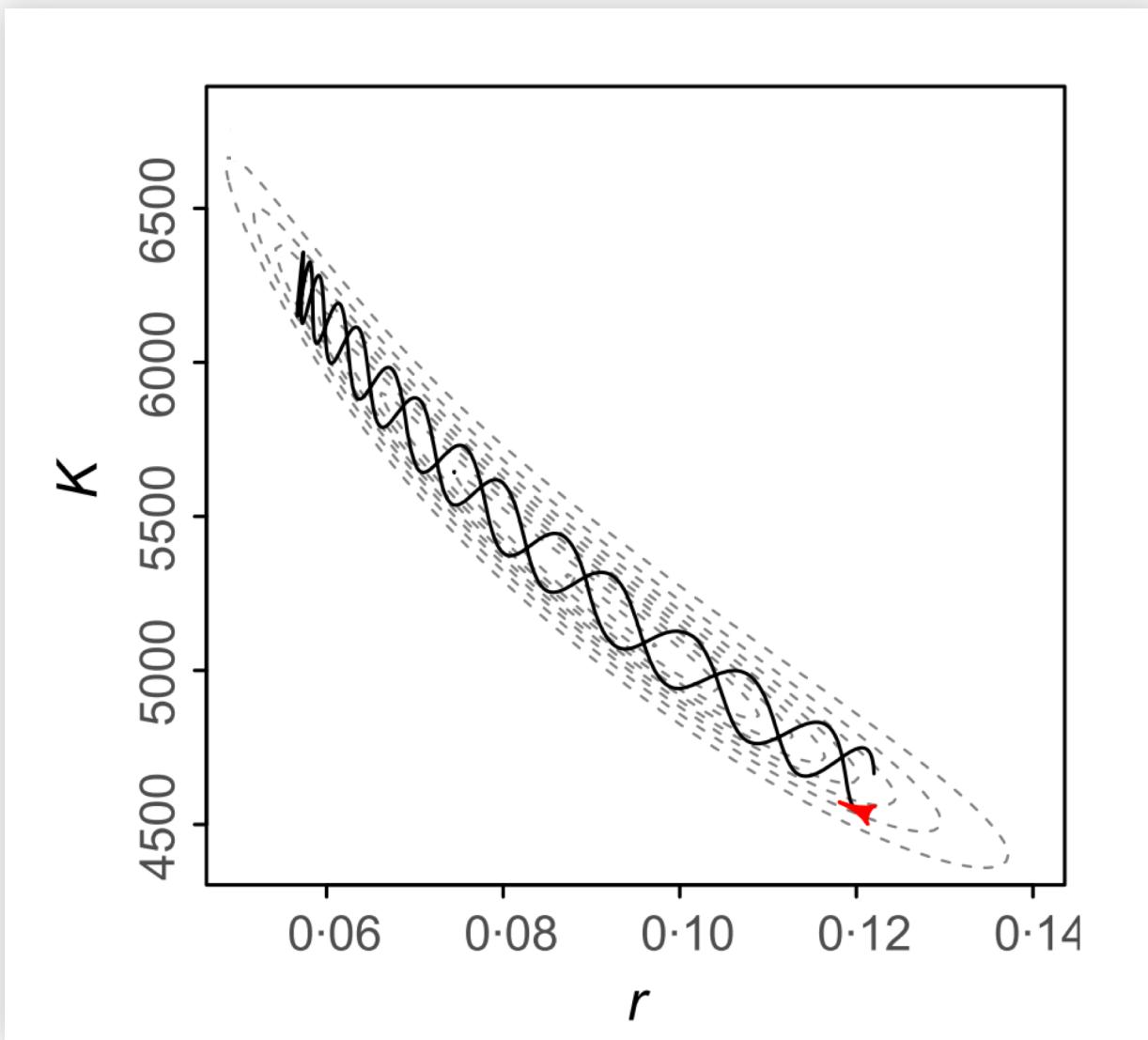
JAGS

```
for(j in 1 : J) {  
    y[j] ~ dbin(p[j], n[j])  
    logit(p[j]) <- theta[1] + theta[2] * x[j]  
    x[j] ~ dnorm(mu[j], tau)  
    mu[j] <- alpha + beta * z[j]  
}  
theta[1] ~ dnorm(0.0, 0.001)  
theta[2] ~ dnorm(0.0, 0.001)
```

greta

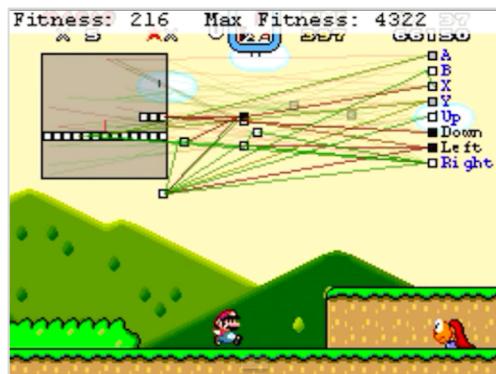
```
theta = normal(0, 32, dim = 2)  
mu <- alpha + beta * z  
x = normal(mu, sigma)  
p <- ilogit(theta[1] + theta[2] * x)  
distribution(y) = binomial(n, p)
```

gradient-based inference



google tensorflow

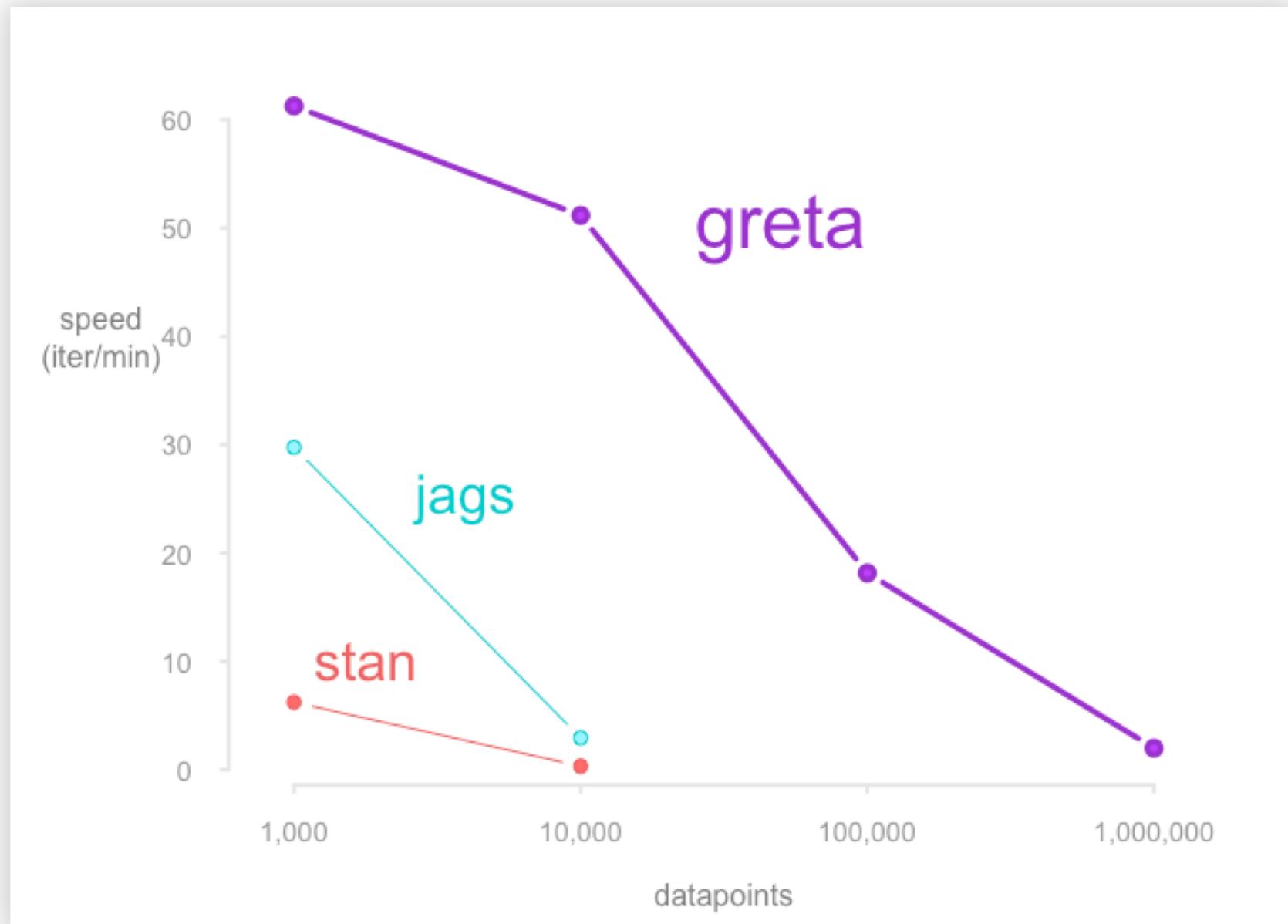
- automatic differentiation
- efficient linear algebra
- highly parallel



Google
Translate

scalable

probit regression with 50 predictors



extendable

[greta.dynamics](#)

a greta extension for modelling dynamical systems

 R  1  2 Updated 12 days ago

[greta.gp](#)

a greta extension for Gaussian process modelling

 R  4  1 Updated on 9 Sep

[greta.multivariate](#)

a greta extension for multivariate modelling

 1 Updated on 26 Aug

[greta.gam](#)

a greta extension for generalised additive modelling using mgcv

 R  3  2 Updated on 23 Aug

extendable

greta.gp

Gaussian processes in greta

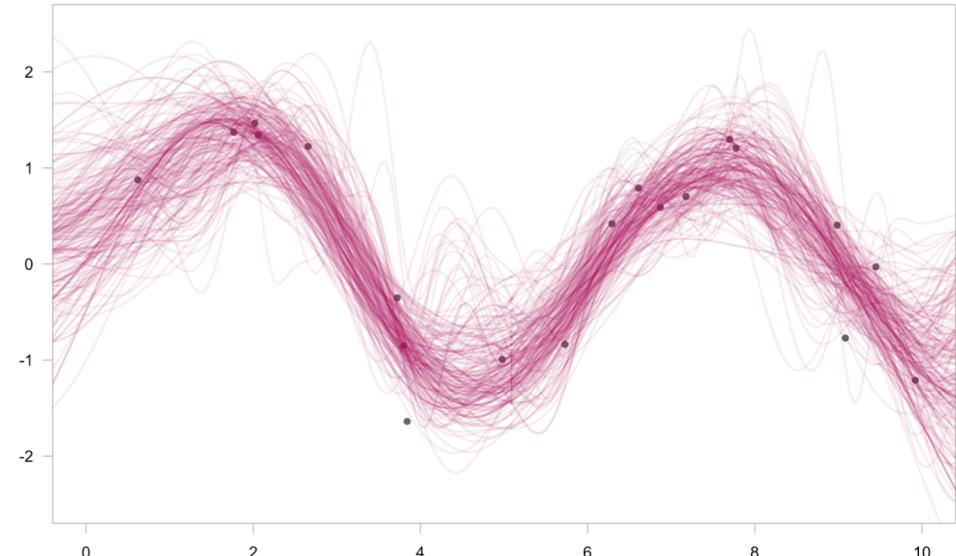
`greta.gp` extends greta to let you define Gaussian processes as part of your model. It provides a syntax to create and combine GP kernels, and use them to define either full rank or sparse Gaussian processes.

[build](#) passing [codecov](#) 98%

```
# kernel & GP
kernel <- rbf(rbf_len, rbf_var) + bias(1)
f = gp(x, kernel)

# likelihood
distribution(y) = normal(f, obs_sd)

# prediction
f_plot <- project(f, x_plot)
```



github.com/greta-dev/greta.gp

what next?

- variational inference
- samplers for big data
- discrete samplers
- differential equations

why ‘greta’?

Grete Hermann (1901-1984)

wrote the first algorithms for computer algebra

... without a computer

(I didn't want people saying 'greet', so spelled the package *greta* instead)

