

# Modelling with RStan

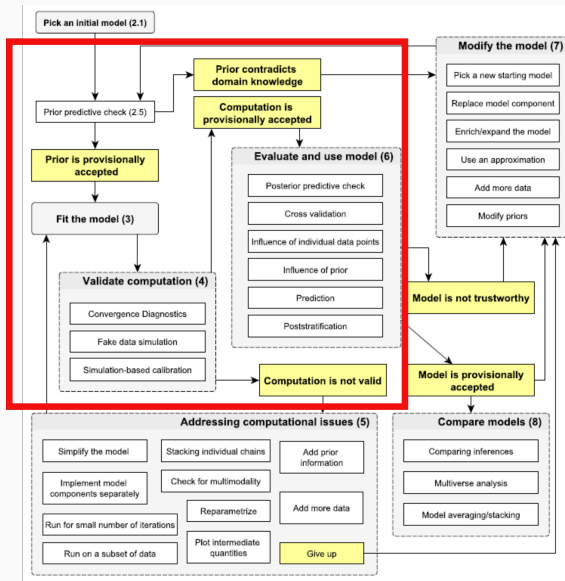
---

Sydney Dimmock

June 13, 2022

1. Choose an initial model.
2. Construct Stan model.
3. Sample the model.
4. Check for convergence and good sampling quality.
  - Unsuccessful? Try a different parameterisation and review of the prior model!
5. Extract and interpret posterior parameters.

# Bayesian Workflow



# Structure of a Stan Model

## Stan Example

```
data{  
  ...  
}  
parameters{  
  ...  
}  
transformed parameters{  
  ...  
}  
model{  
  ...  
}  
generated quantities{  
  ...  
}
```

# Data and Model

We have a dataset containing the number of observed head counts for twenty biased coins:

ID	Flips	Heads	P
1	35	20	0.50
2	61	61	0.99
3	72	31	0.46
4	62	51	0.77
5	48	6	0.25
6	41	39	0.95
7	93	29	0.35

... and so on.

We can construct a mathematical model for this data:

$$y_i \sim \text{Binomial}(n_i, \theta_i), \quad i \dots N$$

$$\theta_i \sim \text{Beta}(\alpha, \beta)$$

**How does this translate into a Stan model?**

# Constructing a Stan Model

## Stan Example

```
data{  
  int N;  
  int y[N];  
  int n[N];  
}
```

# Constructing a Stan Model

## Stan Example

```
data{
  int N;
  int y[N];
  int n[N];
}
parameters{
  real<lower=0, upper=1> theta[N];
}
```



# Constructing a Stan Model

## Stan Example

```
data{
  int N;
  int y[N];
  int n[N];
}
parameters{
  real<lower=0, upper=1> theta[N];
}
model{
  theta ~ beta(2,2);
}
```

# Constructing a Stan Model

## Stan Example

```
data{
  int N;
  int y[N];
  int n[N];
}
parameters{
  real<lower=0, upper=1> theta[N];
}
model{
  theta ~ beta(2,2);
  y ~ binomial(n, theta);
}
```

# Constructing a Stan Model

## Stan Example

```
data{
  int N;
  int y[N];
  int n[N];
}
parameters{
  real<lower=0, upper=1> theta[N];
}
model{
  theta ~ beta(2,2);
  y ~ binomial(n, theta);
}
generated quantities{
  int yrep[N];
  for(i in 1:N){
    yrep[i] = binomial_rng(n[i], theta[i]);
  }
}
```

# Sampling Statements

The model section is made up of sampling statements:

## Stan Example

```
y ~ normal(0,1)
```

Using the distributions are short hands for incrementing the log density:

## Stan Example

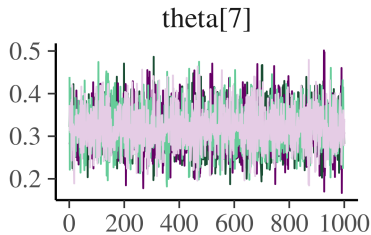
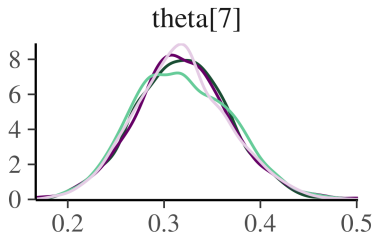
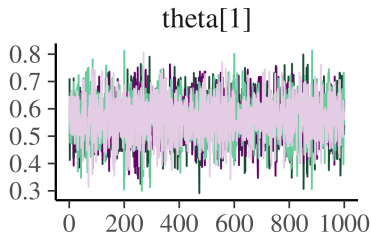
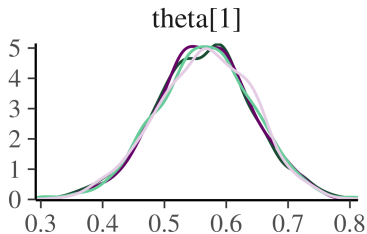
```
target += normal_lpdf( y | 0, 1);
```

**This is how you can define your own densities within Stan.**

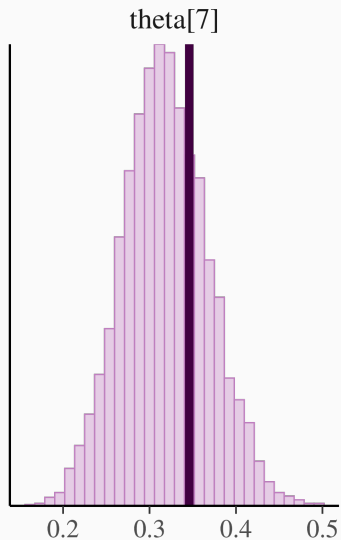
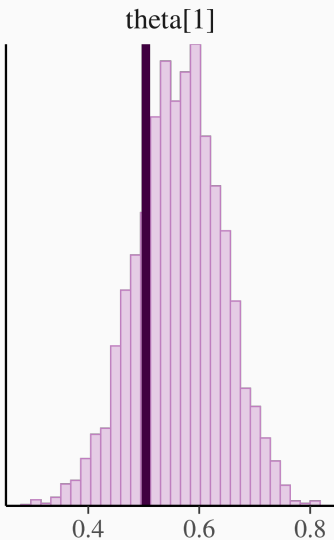
# Running the Model from R

```
1 library(rstan)
2 library(readr)
3 library(bayesplot)
4 rstan_options(auto_write = TRUE)
5 options(mc.cores = parallel::detectCores())
6
7 data <- read_csv("data/coin.csv") # Read in the data
8
9 # Prepare data for Stan
10 stan_data <- list(N = nrow(data),
11                  y = data$Heads,
12                  n = data$Flips)
13
14 # Sample the model
15 fit <- stan(file="models/binom_coin.stan", data=stan_data, chains=4, iter=1000)
16
17 # Extract posterior samples
18 theta <- extract(fit, "theta")$theta
```

# Plotting



# Plotting



Visualisations can be created quickly using `bayesplot`.

The syntax is consistent across most of the library functions requiring:

1. Stan fit object
2. Parameters of interest, specified by string or regular expression.

## Stan Example

```
mcmc_areas(fit, c('theta[1]', 'theta[2]'));
```