

6.8 constructive choice models

Chris Parrish

July 3, 2016

Contents

constructive choice models	1
data	1
model	2
fit	2

6.8 constructive choice models

reference:

- ARM chapter 06, github

```
library(rstan)
rstan_options(auto_write = TRUE)
options(mc.cores = parallel::detectCores())
library(ggplot2)
```

constructive choice models

data

```
source("wells.data.R", echo = TRUE)

##
## > "switc" <- c(1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
## + 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
## + 1, 0, 0, 1, 0, 1, 1, 0, 1 .... [TRUNCATED]
##
## > "arsenic" <- c(2.36, 0.71, 2.07, 1.15, 1.1, 3.9, 2.97,
## + 3.24, 3.28, 2.52, 3.13, 3.04, 2.91, 3.21, 1.7, 1.8, 1.44,
## + 1.43, 2.33, 2.83, 1.7 .... [TRUNCATED]
##
## > "dist" <- c(16.826000213623, 47.3219985961914, 20.9669990539551,
## + 21.4860000610352, 40.8740005493164, 69.5179977416992, 80.7109985351563,
## + .... [TRUNCATED]
##
## > "assoc" <- c(0, 0, 0, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1,
## + 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0,
## + 1, 0, 0, 1, 1, 0, 1, 0, 0 .... [TRUNCATED]
##
## > "educ" <- c(0, 0, 10, 12, 14, 9, 4, 10, 0, 0, 5, 0,
## + 0, 0, 0, 7, 7, 7, 0, 10, 7, 0, 5, 0, 8, 8, 10, 16, 10, 10,
## + 10, 10, 0, 0, 0, 3, 0, .... [TRUNCATED]
##
## > "N" <- 3020
```

model

wells_logit.stan

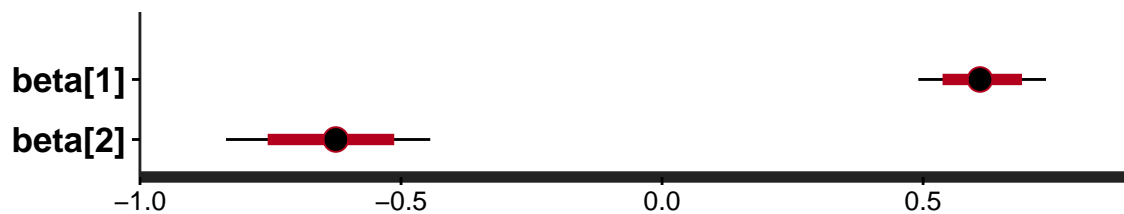
```
data {
  int<lower=0> N;
  vector[N] dist;
  int<lower=0,upper=1> switc[N];
}
transformed data {
  vector[N] dist100;
  dist100 = dist / 100.0;
}
parameters {
  vector[2] beta;
}
model {
  switc ~ bernoulli_logit(beta[1] + beta[2] * dist100);
}
```

fit

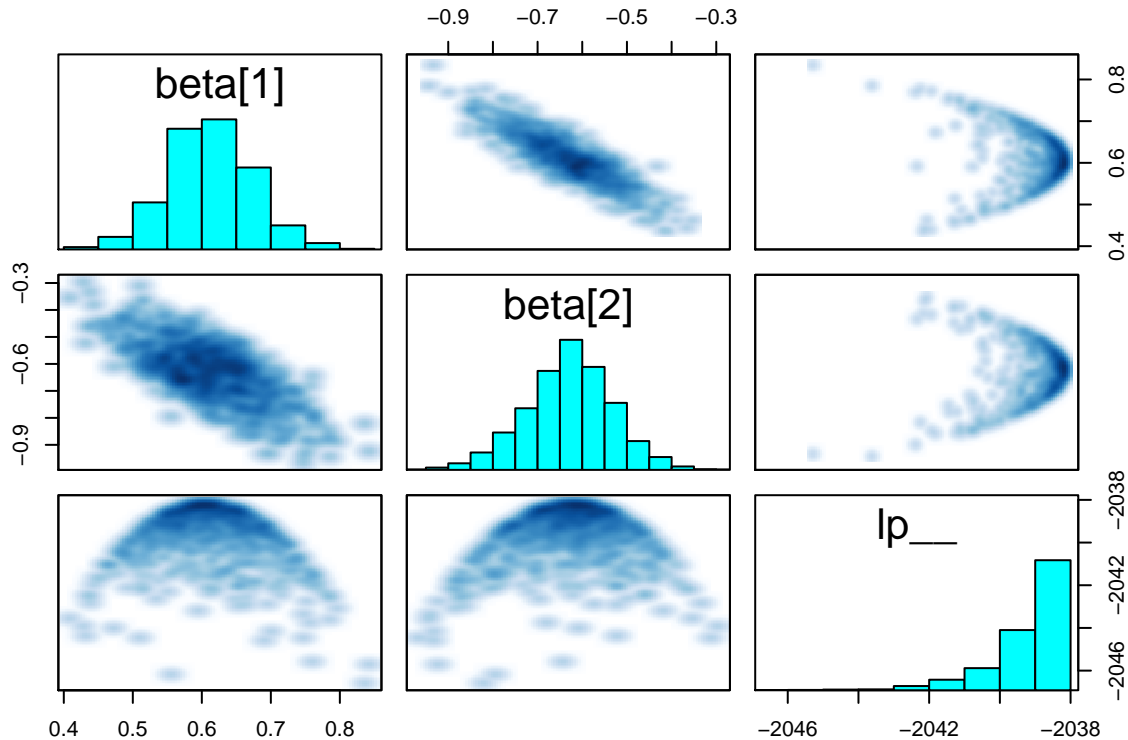
```
## Fitting the model (wells_logit.stan)
## Probit or logit
## glm (switch ~ dist100, family=binomial(link="logit"))
dataList <- c("N","switc","dist")
wells_logit.sf1 <- stan(file='wells_logit.stan', data=dataList,
                       iter=1000, chains=4)
```

```
plot(wells_logit.sf1)
```

```
## ci_level: 0.8 (80% intervals)
## outer_level: 0.95 (95% intervals)
```



```
pairs(wells_logit.sf1)
```



```
print(wells_logit.sf1)
```

```
## Inference for Stan model: wells_logit.
## 4 chains, each with iter=1000; warmup=500; thin=1;
## post-warmup draws per chain=500, total post-warmup draws=2000.
##
##           mean se_mean  sd    2.5%    25%    50%    75%    97.5%
## beta[1]   0.61   0.00 0.06   0.49   0.57   0.61   0.65   0.74
## beta[2]  -0.63   0.00 0.10  -0.84  -0.69  -0.62  -0.57  -0.44
## lp__    -2039.18  0.04 1.10 -2042.06 -2039.56 -2038.82 -2038.40 -2038.14
##           n_eff Rhat
## beta[1]   654 1.00
## beta[2]   575 1.01
## lp__     958 1.01
##
## Samples were drawn using NUTS(diag_e) at Wed Jul 6 09:47:43 2016.
## For each parameter, n_eff is a crude measure of effective sample size,
## and Rhat is the potential scale reduction factor on split chains (at
## convergence, Rhat=1).
## The estimated Bayesian Fraction of Missing Information is a measure of
## the efficiency of the sampler with values close to 1 being ideal.
## For each chain, these estimates are
## 0.9 0.7 0.8 1.4
```