Assignment 8

Anonymous

Contents

1.	Fitting of the models	2
2.	Computation of the PSIS-LOO elpd values and the \hat{k} -values	6
3.	Computation of the effective number of parameters p_{eff}	7
4.	Assessment of how reliable the PSIS-LOO estimates are for the three models based on the $\hat{k}\text{-values}$	8
5.	Model selection according to PSIS-LOO	8

Load packages and import data

```
library(aaltobda)
library(cmdstanr)
library(loo)
library(bayesplot)
library(ggplot2)
library(posterior)

data("factory")
```

1. Fitting of the models

• Separate model

```
separate_m <- cmdstan_model(stan_file="separate_model.stan")</pre>
separate_m
data {
  int<lower=0> N; // number of observations
  int<lower=0> K; // number of groups
  array[N] int<lower=1, upper=K> g; // discrete group indicators
  vector<lower=0>[N] y; // observations
parameters {
  vector[K] mu; // group means
  vector<lower=0>[K] sigma; // group standard deviations
}
model {
  mu ~ normal(0, 10);
  sigma ~ gamma(1,1);
  y ~ normal(mu[g], sigma[g]);
generated quantities {
  real ypred;
  vector[N] log_lik;
  for (i in 1:N)
    log_lik[i] = normal_lpdf(y[i] | mu[g[i]], sigma[g[i]]);// predictive distribution for the sixth mac
  ypred = normal_rng(mu[6], sigma[6]);
separate_data <- list(</pre>
 N = 6 * nrow(factory),
 K = ncol(factory),
 g = rep(1:6, nrow(factory)),
  y = c(t(factory[,1:6]))
```

```
fit_separate <- separate_m$sample(data=separate_data, refresh=1000, seed=42)
Running MCMC with 4 sequential chains...
Chain 1 Iteration:
                      1 / 2000 [ 0%]
                                        (Warmup)
Chain 1 Iteration: 1000 / 2000 [ 50%]
                                        (Warmup)
Chain 1 Iteration: 1001 / 2000 [ 50%]
                                        (Sampling)
Chain 1 Iteration: 2000 / 2000 [100%]
                                        (Sampling)
Chain 1 finished in 0.5 seconds.
Chain 2 Iteration:
                      1 / 2000 [ 0%]
                                        (Warmup)
Chain 2 Iteration: 1000 / 2000 [ 50%]
                                        (Warmup)
Chain 2 Iteration: 1001 / 2000 [ 50%]
                                        (Sampling)
Chain 2 Iteration: 2000 / 2000 [100%]
                                        (Sampling)
Chain 2 finished in 0.4 seconds.
Chain 3 Iteration:
                     1 / 2000 [ 0%]
                                        (Warmup)
Chain 3 Iteration: 1000 / 2000 [ 50%]
                                        (Warmup)
Chain 3 Iteration: 1001 / 2000 [ 50%]
                                        (Sampling)
Chain 3 Iteration: 2000 / 2000 [100%]
                                        (Sampling)
Chain 3 finished in 0.4 seconds.
                      1 / 2000 [ 0%]
Chain 4 Iteration:
                                        (Warmup)
Chain 4 Iteration: 1000 / 2000 [ 50%]
                                        (Warmup)
Chain 4 Iteration: 1001 / 2000 [ 50%]
                                        (Sampling)
Chain 4 Iteration: 2000 / 2000 [100%]
                                        (Sampling)
Chain 4 finished in 0.4 seconds.
All 4 chains finished successfully.
Mean chain execution time: 0.4 seconds.
Total execution time: 2.1 seconds.
  · Pooled model
pooled_m <- cmdstan_model(stan_file="pooled_model.stan")</pre>
pooled_m
data {
  int<lower=0> N; // number of observations
  vector<lower=0>[N] y; // observations
}
parameters {
  real mu;
  real<lower=0> sigma;
}
model {
 mu ~ normal(0, 10);
  sigma ~ gamma(1,1);
  y ~ normal(mu, sigma);
generated quantities {
 real ypred;
```

```
vector[N] log_lik;
  for (i in 1:N)
    log_lik[i] = normal_lpdf(y[i] | mu, sigma); // predictive distribution for the sixth machine
 ypred = normal_rng(mu, sigma);
}
pooled_data <- list(</pre>
 N = 6 * nrow(factory),
 y = c(t(factory[,1:6]))
fit_pooled <- pooled_m$sample(data=pooled_data, refresh=1000, seed=42)
Running MCMC with 4 sequential chains...
Chain 1 Iteration:
                      1 / 2000 [ 0%]
                                        (Warmup)
Chain 1 Iteration: 1000 / 2000 [ 50%]
                                        (Warmup)
Chain 1 Iteration: 1001 / 2000 [ 50%]
                                        (Sampling)
Chain 1 Iteration: 2000 / 2000 [100%]
                                        (Sampling)
Chain 1 finished in 0.1 seconds.
Chain 2 Iteration:
                      1 / 2000 [ 0%]
                                        (Warmup)
Chain 2 Iteration: 1000 / 2000 [ 50%]
                                        (Warmup)
Chain 2 Iteration: 1001 / 2000 [ 50%]
                                        (Sampling)
Chain 2 Iteration: 2000 / 2000 [100%]
                                        (Sampling)
Chain 2 finished in 0.1 seconds.
Chain 3 Iteration: 1 / 2000 [ 0%]
                                        (Warmup)
Chain 3 Iteration: 1000 / 2000 [ 50%]
                                        (Warmup)
Chain 3 Iteration: 1001 / 2000 [ 50%]
                                        (Sampling)
Chain 3 Iteration: 2000 / 2000 [100%]
                                        (Sampling)
Chain 3 finished in 0.1 seconds.
Chain 4 Iteration:
                      1 / 2000 [ 0%]
                                        (Warmup)
Chain 4 Iteration: 1000 / 2000 [ 50%]
                                        (Warmup)
Chain 4 Iteration: 1001 / 2000 [ 50%]
                                        (Sampling)
Chain 4 Iteration: 2000 / 2000 [100%]
                                        (Sampling)
Chain 4 finished in 0.1 seconds.
All 4 chains finished successfully.
Mean chain execution time: 0.1 seconds.
Total execution time: 0.7 seconds.
  • Hierarchical model
hierarchical_m <- cmdstan_model(stan_file="hierarchical_model.stan")</pre>
hierarchical_m
data {
  int<lower=0> N; // number of observations
  int<lower=0> K; // number of groups
  array[N] int<lower=1, upper=K> g; // discrete group indicators
  vector<lower=0>[N] y; // observations
}
```

```
parameters {
  real mu0;
  vector[K] mu;
  real<lower=0> sigma;
}
model {
  mu0 ~ normal(0, 10);
  sigma ~ gamma(1,1);
  mu ~ normal(mu0, sigma);
  y ~ normal(mu[g], sigma);
generated quantities {
  real ypred;
  vector[N] log_lik;
  for (i in 1:N)
    log_lik[i] = normal_lpdf(y[i] | mu[g[i]], sigma);// predictive distribution for the sixth machine
  ypred = normal_rng(mu[6], sigma);
}
hierarchical_data <- list(
 N = 6 * nrow(factory),
 K = ncol(factory),
 g = rep(1:6, nrow(factory)),
  y = c(t(factory[,1:6]))
fit_hierarchical <- hierarchical_m$sample(data=hierarchical_data, refresh=1000, seed=42)
Running MCMC with 4 sequential chains...
Chain 1 Iteration:
                      1 / 2000 [ 0%]
                                        (Warmup)
Chain 1 Iteration: 1000 / 2000 [ 50%]
                                        (Warmup)
Chain 1 Iteration: 1001 / 2000 [ 50%]
                                        (Sampling)
Chain 1 Iteration: 2000 / 2000 [100%]
                                        (Sampling)
Chain 1 finished in 0.2 seconds.
Chain 2 Iteration:
                      1 / 2000 [ 0%]
                                        (Warmup)
Chain 2 Iteration: 1000 / 2000 [ 50%]
                                        (Warmup)
Chain 2 Iteration: 1001 / 2000 [ 50%]
                                        (Sampling)
Chain 2 Iteration: 2000 / 2000 [100%]
                                        (Sampling)
Chain 2 finished in 0.2 seconds.
Chain 3 Iteration:
                      1 / 2000 [ 0%]
                                        (Warmup)
Chain 3 Iteration: 1000 / 2000 [ 50%]
                                        (Warmup)
Chain 3 Iteration: 1001 / 2000 [ 50%]
                                        (Sampling)
Chain 3 Iteration: 2000 / 2000 [100%]
                                        (Sampling)
Chain 3 finished in 0.2 seconds.
Chain 4 Iteration:
                      1 / 2000 [ 0%]
                                        (Warmup)
Chain 4 Iteration: 1000 / 2000 [ 50%]
                                        (Warmup)
Chain 4 Iteration: 1001 / 2000 [ 50%]
                                        (Sampling)
Chain 4 Iteration: 2000 / 2000 [100%]
                                        (Sampling)
Chain 4 finished in 0.3 seconds.
```

```
All 4 chains finished successfully.

Mean chain execution time: 0.2 seconds.

Total execution time: 1.2 seconds.
```

2. Computation of the PSIS-LOO elpd values and the \hat{k} -values

• Separate model

```
separate_loo <- fit_separate$loo()
```

Warning: Some Pareto k diagnostic values are slightly high. See help('pareto-k-diagnostic') for details

```
separate_loo
```

Computed from 4000 by 30 log-likelihood matrix

```
Estimate SE
elpd_loo -196.8 8.0
p_loo 19.8 1.5
looic 393.6 15.9
```

Monte Carlo SE of elpd_loo is 0.1.

Pareto k diagnostic values:

```
Count Pct.
                                       Min. n_eff
(-Inf, 0.5]
                         26
                               86.7%
              (good)
                                       538
 (0.5, 0.7]
              (ok)
                               13.3%
                                       461
   (0.7, 1]
              (bad)
                          0
                                0.0%
                                       <NA>
   (1, Inf)
                                0.0%
              (very bad) 0
                                       <NA>
```

All Pareto k estimates are ok (k < 0.7). See help('pareto-k-diagnostic') for details.

PSIS-LOO elpd is -197.

- 4 \hat{k} -values are between 0.5 and 0.7 and 26 values are lower than 0.5.
 - Pooled model

```
pooled_loo <- fit_pooled$loo()
pooled_loo</pre>
```

Computed from 4000 by 30 log-likelihood matrix

```
Estimate SE
elpd_loo -134.5 4.9
p_loo 2.5 0.8
looic 269.0 9.9
```

```
Monte Carlo SE of elpd_loo is 0.1. All Pareto k estimates are good (k < 0.5). See help('pareto-k-diagnostic') for details.  PSIS-LOO \ elpd \ is \ -135  All \hat{k}-values are lower than 0.5.
```

• Hierarchical model

```
hierarchical_loo <- fit_hierarchical$loo()
hierarchical_loo</pre>
```

Computed from 4000 by 30 log-likelihood matrix

```
Estimate SE
elpd_loo -127.9 3.0
p_loo 5.5 1.0
looic 255.8 5.9
-----
Monte Carlo SE of elpd_loo is 0.1.

All Pareto k estimates are good (k < 0.5).
See help('pareto-k-diagnostic') for details.
```

PSIS-LOO elpd is -128

All \hat{k} -values are lower than 0.5.

3. Computation of the effective number of parameters p_{eff}

• Separate model

separate_loo\$estimates

```
Estimate SE
elpd_loo -196.78922 7.953282
p_loo 19.82498 1.466361
looic 393.57843 15.906563
```

 p_{eff} for separate model is 19.8.

• Pooled model

pooled_loo\$estimates

```
Estimate SE
elpd_loo -134.522760 4.9254797
p_loo 2.527918 0.8485453
looic 269.045520 9.8509593
```

 p_{eff} for pooled model is 2.5.

• Hierarchical model

hierarchical_loo\$estimates

```
Estimate SE
elpd_loo -127.904448 2.957054
p_loo 5.549513 1.026310
looic 255.808896 5.914107
```

 p_{eff} for hierarchical model is 5.5.

4. Assessment of how reliable the PSIS-LOO estimates are for the three models based on the \hat{k} -values

All the PSIS-LOO estimates are reliable because all the \hat{k} -values are lower or equal than 0.7 in the presented models.

5. Model selection according to PSIS-LOO

The separate model has the worst $elpd_{loo}$ cv equal to -197.

Pooled and hierarchical models has almost equal estimations: 269 and 256 $elpd_{loo}$ cv.

Let's compare these two models:

loo_compare(pooled_loo, hierarchical_loo)

```
elpd_diff se_diff
model2 0.0 0.0
model1 -6.6 3.9
```

We got that the hierarchical model gave the better result, thus, it should be selected.