

Practical 7. PSA to structural uncertainty — SOLUTIONS

Lecture 7

 PDF version

The first thing we do is loading and analysing the “base-case” model, which is stored in the object `statins_base.Rdata` and the “robust” version of the model, stored in `statins_HC.Rdata`.

```
library(BCEA)
library(R2OpenBUGS)
load("statins_base.Rdata")
load("statins_HC.Rdata")
```

We can use the R function `print` to visualise the output for the two models, for example as in the following.

```
print(statins_base)
```

The output to this call is a long list of summary statistics — it is also possible to visualise an excerpt by using code such as the following

```
head(statins_base$summary[,c("mean", "sd", "2.5%", "97.5%", "Rhat", "n.eff")],n=15)
```

	mean	sd	2.5%	97.5%	Rhat	n.eff
cost.hosp[1]	238.7010	137.0428	91.68029	482.0066	1.001533	980
cost.hosp[2]	315.6340	168.7579	124.20521	668.4667	1.002554	1000
cost.hosp[3]	523.0695	451.0165	144.02705	1357.9918	1.002820	1000
cost.hosp[4]	424.9861	232.1917	170.08732	877.9484	1.001743	980
cost.hosp[5]	305.1978	172.3249	120.79156	656.3935	1.002747	550
cost.hosp[6]	301.1282	163.4569	121.85935	618.0017	1.001342	1000
cost.stat[1]	480.8821	289.1621	137.50194	1232.7586	1.004167	360
cost.stat[2]	350.0194	201.6103	103.42871	871.5393	1.000252	1000
cost.stat[3]	166.6851	125.6502	34.24849	498.3156	1.000219	1000
cost.stat[4]	305.4061	261.7113	47.69648	1008.5598	1.004566	1000
cost.stat[5]	346.9371	209.6277	103.21293	880.0139	1.006177	400
cost.stat[6]	165.0717	129.7352	35.28509	526.9310	1.000074	1000
cost.tot[1]	719.5831	324.8498	309.13357	1526.9058	1.005610	270
cost.tot[2]	665.6534	265.4862	331.33786	1357.5038	1.001748	1000
cost.tot[3]	689.7546	467.3877	242.54283	1629.7467	1.002190	1000

which produces the first `n=15` rows (i.e. parameters) for the whole summary table. In particular, we only select the columns headed as `"mean"`, `"sd"`, etc. (we do so to exclude additional quantiles that are automatically stored in the object `statins_base$summary`). We should make sure that the models have all converged and that autocorrelation is not an issue (by e.g. analysing the \hat{R} and n_{eff} statistics).

We can already check the DIC associated with each of the two models, to get some ideas of which one will be given most weight in the structural PSA. We can do so by using the following command.

```
# Displays the DIC for the two models
c(statins_base$DIC,statins_HC$DIC)
```

```
[1] 2233.875 2225.988
```

As is easy to see, the “robust” model is associated with a relatively lower DIC (by over 10 points).

We can now move on and use the results from the two Bayesian models as inputs to `BCEA`. The objects `statins_base$sims.list` and `statins_HC$sims.list` contain the simulated values for all the model parameters monitored in `list` format. We can follow the script and use the code

```
# Defines the intervention labels
interventions <- c("Atorvastatin", "Fluvastatin", "Lovastatin", "Pravastatin",
                  "Rosuvastatin", "Simvastatin")

# BCEA object with the economic analysis of the "base case" model
m1 <- bcea(statins_base$sims.list$effect, statins_base$sims.list$cost.tot,
          ref=1, interventions=interventions)

# BCEA object with the economic analysis of the Half-Cauchy model
m2 <- bcea(statins_HC$sims.list$effect, statins_HC$sims.list$cost.tot,
          ref=1, interventions=interventions)
```

to first define a vector of intervention labels and then apply the function `bcea` to the suitable variables of effects and costs in the two models.

The two objects `m1` and `m2` can be post-processed as any `BCEA` objects (e.g. using `plot` or `print` methods). But in addition to this, we can also combine them to perform the PSA to structural assumptions. To do so, we need to manipulate the original objects in a suitable way. Firstly, we need to create a `list` of models, which we can simply do using the following command.

```
# Combines the BUGS models
models <- list(statins_base, statins_HC)
```

the newly created object contains the information from the two `BUGS` models. We can also create suitable lists in which we store the relevant variables of effectiveness and costs from the two models, for example using code such as the following.

```
# Creates the variables of effectiveness and costs
effects <- list(statins_base$sims.list$effect, statins_HC$sims.list$effect)
costs <- list(statins_base$sims.list$cost.tot, statins_HC$sims.list$cost.tot)
```

Finally, we can feed these inputs to the `BCEA` function `struct.psa` as in the following.

```
# Finally uses BCEA to perform the structural PSA to consider the base and HC models
m3 <- struct.psa(models, effects, costs, ref=1, interventions=interventions)
```

`struct.psa` takes as basic arguments three lists, containing the `BUGS` models, the list of effects and the list of costs simulations and combines them to compute the model weights (based on the DICs).

The object `m3` is a `list`, which contains 3 elements:

```
lapply(m3, function(x) list(class(x), names(x)))
```

```

$he
$he[[1]]
[1] "bcea" "list"

$he[[2]]
[1] "n_sim"      "n_comparators" "n_comparisons" "delta_e"
[5] "delta_c"    "ICER"          "Kmax"          "k"
[9] "ceac"       "ib"            "eib"           "kstar"
[13] "best"       "U"             "vi"            "Ustar"
[17] "ol"         "evi"           "ref"           "comp"
[21] "step"       "interventions" "e"             "c"

$w
$w[[1]]
[1] "numeric"

$w[[2]]
NULL

$DIC
$DIC[[1]]
[1] "numeric"

$DIC[[2]]
NULL

```

The R function `lapply` applies iteratively the function `class` and `names` to each element of the object `m3`.

As is possible to see, the first one, named `he`, is an object in the class `BCEA` and so it contains the usual elements that such objects do (e.g. `n.sim`, `n.comparators`, etc). The elements `w` and `DIC` are numeric vectors and include the weights and the value of the DIC associated with each individual models. We can visualise for example the weights by using the command,

```
print(m3$w)
```

```
[1] 0.01901127 0.98098873
```

which indicates that the second model (the “robust” Half-Cauchy) is given a weight of over 98%. This is consistent with the fact that its DIC is lower than the one for the base case model, which in turn indicates better fit.

We can also use all the methods implemented for `BCEA` objects to analyse and visualise the output of the model averaging. For example, we can summarise the cost-effectiveness analysis by typing

```
summary(m3$he)
```

Cost-effectiveness analysis summary

Reference intervention: Atorvastatin

Comparator intervention(s): Fluvastatin
: Lovastatin
: Pravastatin
: Rosuvastatin
: Simvastatin

Optimal decision: choose Simvastatin for $k < 19129.49$ and for $k \geq 3919.60$

Analysis for willingness to pay parameter $k = 25000$

	Expected utility
Atorvastatin	22823
Fluvastatin	22435
Lovastatin	21381
Pravastatin	21731
Rosuvastatin	22526
Simvastatin	22738

	EIB	CEAC	ICER
Atorvastatin vs Fluvastatin	388.695	0.768	3919.60
Atorvastatin vs Lovastatin	1442.154	0.843	1432.44
Atorvastatin vs Pravastatin	1092.152	0.958	336.72
Atorvastatin vs Rosuvastatin	297.304	0.738	5227.07
Atorvastatin vs Simvastatin	85.002	0.594	19129.49

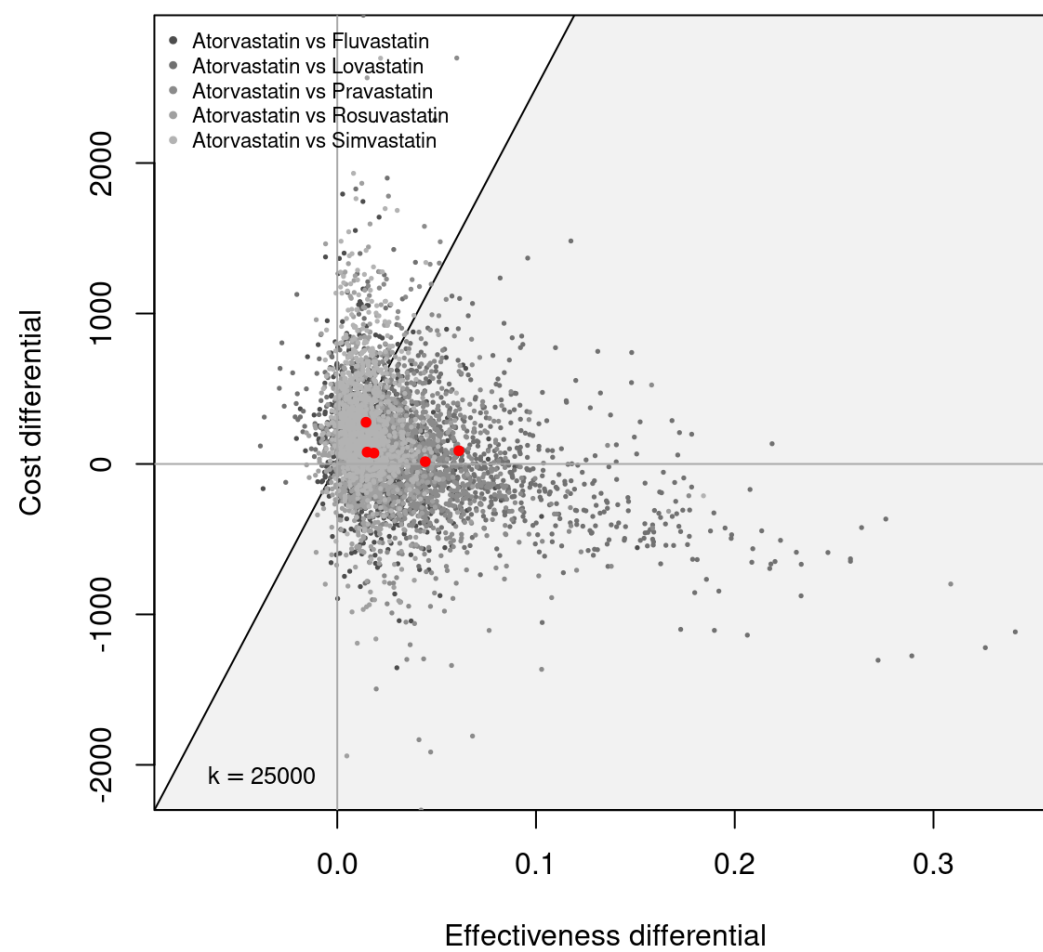
Optimal intervention (max expected utility) for $k = 25000$: Atorvastatin

EVPI 193.22

and we could plot the cost-effectiveness plane with the following command.

```
ceplane.plot(m3$he)
```

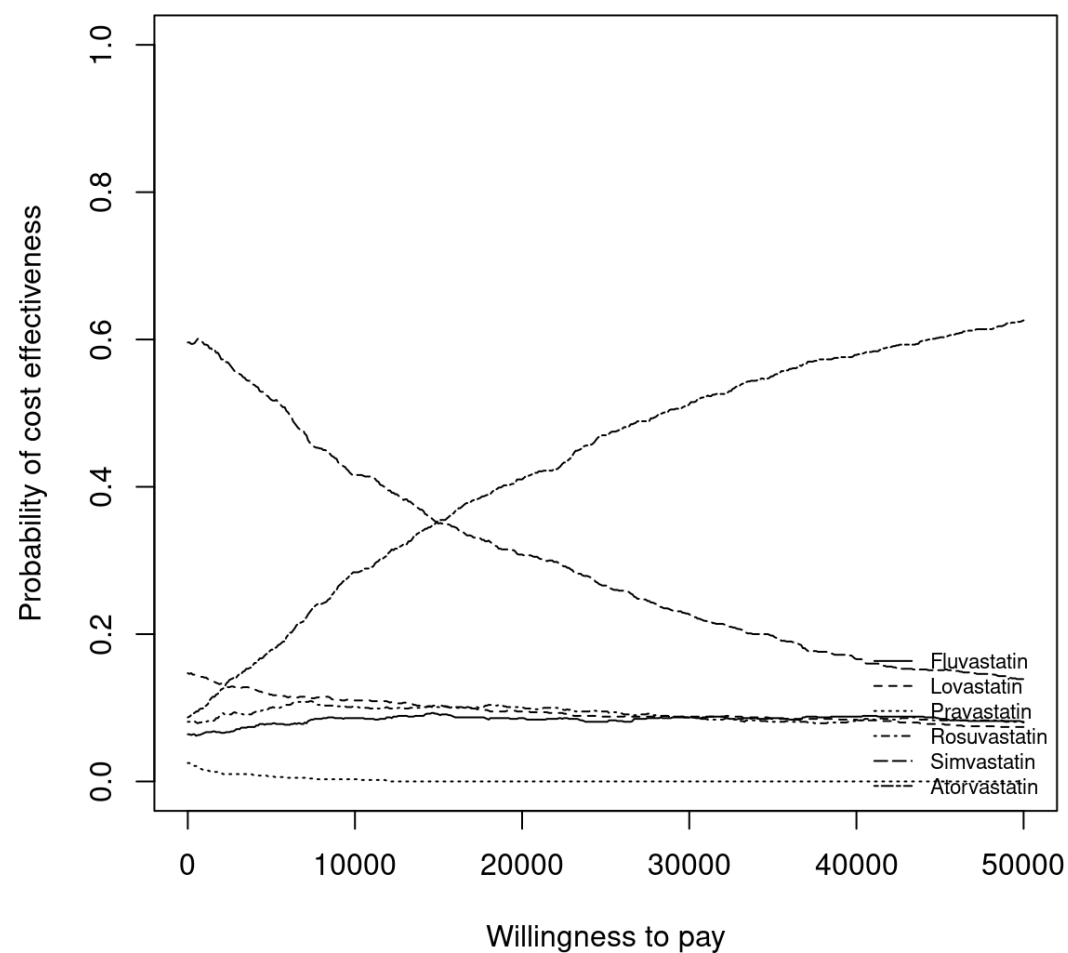
Cost-Effectiveness Plane



or generate multiple treatments comparison cost-effectiveness acceptability curves with the following commands.

```
m3.multi<-multi.ce(m3$he)
ceac.plot(m3.multi)
```

Cost Effectiveness Acceptability Curve



Notice that because *in this particular case* one of the models is effectively given an almost 100% weight, the model average will resemble it almost identically.