

A dip into R for decision modelling

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1

Live Content Slide

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Poll: What software do you mostly use for cost-effectiveness analysis?

Live Content Slide

When playing as a slideshow, this slide will display live content

Poll: Do you think R is better for cost-effectiveness analysis and modelling than Excel?



Overview

- Heard the wonderful things you can do in R.
- Itching to get your hands dirty?
- We'll now talk through the specifics of programming a (probabilistic) decision tree in R.
- The most boring presentation of ISPOR? We'll see...



Simple functions – logit and its inverse

Logistic link function

```
logit<-function(x)
{
  return(log(x/(1-x)))
}
```

Inverse of logit

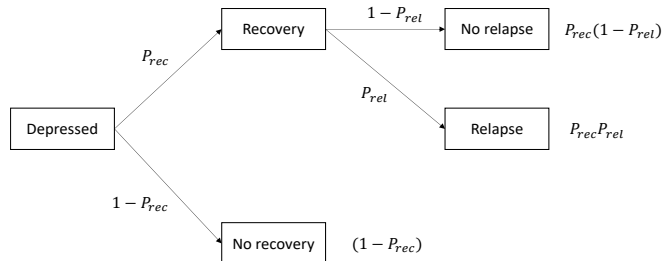
```
expit<-function(x)
{
  return(1/(1+exp(-x)))
}
```

```
R Console
> logit(0)
[1] -Inf
> logit(0.5)
[1] 0
> logit(0.2)
[1] -1.386294
> expit(0)
[1] 0.5
> expit(-1.4)
[1] 0.1978161
> expit(logit(0.2))
[1] 0.2
>
> |
```



5

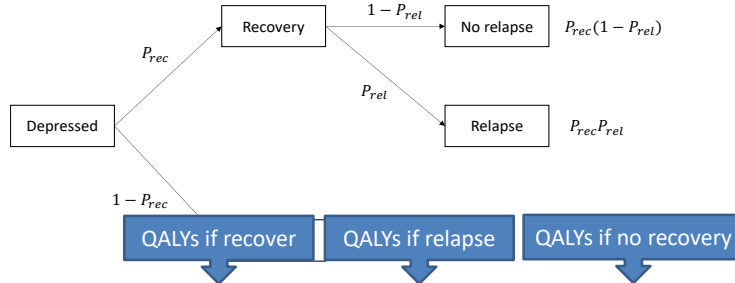
Simple decision tree in R



- Consider this simple decision tree with artificial input parameters.
- Probabilities of recovery and relapse for no treatment (option 1), cognitive behavioural therapy (option 2), and antidepressants (option 3).
- This toy model is available on GitHub:
<https://github.com/Bogdasayen/Depression-toy-decision-tree-in-R>



Implementing a decision tree in R



```

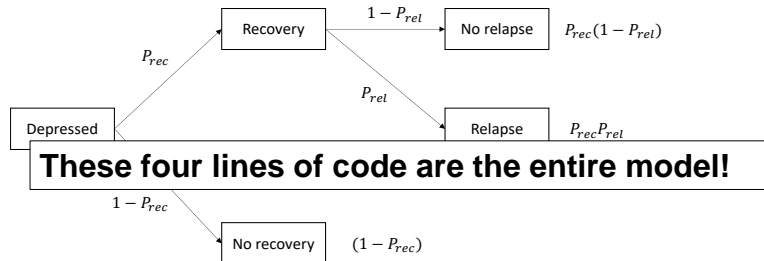
effects<-p.rec*(1-p.rel)*q.rec+p.rec*p.rel*q.rel+(1-p.rec)*q.norec
costs<-c.treat+p.rec*(1-p.rel)*c.rec+p.rec*p.rel*c.rel+(1-p.rec)*c.norec
net.benefit<-lambda*effects-costs
incremental.nb<-net.benefit-net.benefit[,1]

```

Treatment cost
Recovery cost
Relapse cost
No recovery cost

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Implementing a decision tree in R



```

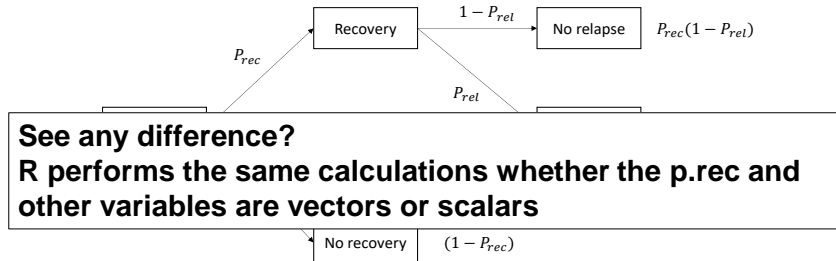
effects<-p.rec*(1-p.rel)*q.rec+p.rec*p.rel*q.rel+(1-p.rec)*q.norec
costs<-c.treat+p.rec*(1-p.rel)*c.rec+p.rec*p.rel*c.rel+(1-p.rec)*c.norec
net.benefit<-lambda*effects-costs
incremental.nb<-net.benefit-net.benefit[,1]

```

And now we make it probabilistic...

NIHR

Making it probabilistic (model code)



```

effects<-p.rec*(1-p.rel)*q.rec+p.rec*p.rel*q.rel+(1-p.rec)*q.norec
costs<-c.treat+p.rec*(1-p.rel)*c.rec+p.rec*p.rel*c.rel+(1-p.rec)*c.norec
net.benefit<-lambda*effects-costs
incremental.nb<-net.benefit-net.benefit[,1]
  
```



Making it probabilistic (Costs, Utilities)

Outcome	Costs	QALYS
Recovery, no relapse	$C_{rec} = N(\mu = 1000, \sigma = 50)$	$Q_{rec} = N(\mu = 26, \sigma = 2)$
Recovery, relapse	$C_{rel} = N(\mu = 2000, \sigma = 100)$	$Q_{rel} = N(\mu = 23, \sigma = 3)$
No recovery	$C_{no\ rec} = N(\mu = 2500, \sigma = 125)$	$Q_{no\ rec} = N(\mu = 20, \sigma = 4)$

```

# Costs for recovery, relapse, and no recovery
c.rec<-rnorm(n=n.samples, mean=1000, sd=50)
c.rel<-rnorm(n=n.samples, mean=2000, sd=100)
c.norec<-rnorm(n=n.samples, mean=2500, sd=125)
  
```

```

# QALYs for recovery, relapse, and no recovery
q.rec<-rnorm(n=n.samples, mean=26, sd=2)
q.rel<-rnorm(n=n.samples, mean=23, sd=3)
q.norec<-rnorm(n=n.samples, mean=20, sd=4)
  
```



Making it probabilistic (Treatment effects)

- Log odds ratios follow multivariate normal

$$\text{Recovery: } \begin{pmatrix} \text{lor}_{2,rec} \\ \text{lor}_{3,rec} \end{pmatrix} \sim MVN \left(\begin{pmatrix} 0.99 \\ 1.33 \end{pmatrix}, \begin{pmatrix} 0.22 & 0.15 \\ 0.15 & 0.20 \end{pmatrix} \right)$$

$$\text{Relapse: } \begin{pmatrix} \text{lor}_{2,rel} \\ \text{lor}_{3,rel} \end{pmatrix} \sim MVN \left(\begin{pmatrix} -1.48 \\ -0.40 \end{pmatrix}, \begin{pmatrix} 0.14 & 0.05 \\ 0.05 & 0.11 \end{pmatrix} \right)$$

- As it's a statistical language, the multivariate normal is implemented simply in R:

```
lor.rec<-mvrnorm(n=n.samples,mu=c(0.99,1.33),
sigma=matrix(c(0.22,0.15,0.15,0.20),nrow=2))
lor.rel<-mvrnorm(n=n.samples,mu=c(-1.48,-0.40),
sigma=matrix(c(0.14,0.05,0.05,0.11),nrow=2))
```



Instead use MCMC via R2OpenBUGS

- Link directly with network meta-analysis code in OpenBUGS (or JAGS/STAN etc.)

```
library(R2OpenBUGS)
```

- Load some BUGS model file

```
source("fixed.effects.binary.R")
```

- Set simulation parameters

```
n.chains<-2; num.sims<-10000*n.chains; burn.in<-50000*n.chains
```

- Call R2OpenBUGS key function

```
bugs.object<-
```

```
bugs(data=bugs.data.recovery,inits=NA,model=fixed.effects.binary...)
```

- Then get parameter samples from bugs.object\$sims.array



Instead MCMC via R2OpenBUGS

- Or load precalculated log odds ratios for recovery (similarly for relapse)

```
mcmc.recovery<-read.csv(file="lor.recovery.bugs.csv")
```

- Can use just the first n.samples of the matrix

```
lor.rec<-mcmc.recovery[1:n.samples,]
```



13

Making it probabilistic (Reference probabilities)

Parameter	No Treatment (Option 1)
P_{rec}	$P_{1,rec} = \text{Beta}(\alpha = 6, \beta = 200)$
P_{rel}	$P_{1,rel} = \text{Beta}(\alpha = 2, \beta = 100)$

- The beta distribution is another of many implemented in base R.
- Note however the idiosyncratic naming convention of the parameters.
- α is *shape1* and β is *shape2*.

```
p.rec[,1]<-rbeta(n=n.samples, shape1=6, shape2=200)
```

```
p.rel[,1]<-rbeta(n=n.samples, shape1=2, shape2=100)
```



14

Making it probabilistic (Comparator probabilities)

Parameter	CBT (Option 2)	Antidepressant (Option 3)
P_{rec}	$P_{2,rec} = \text{expit}(\text{logit}(P_{1,rec}) + \text{lor}_{2,rec})$	$P_{3,rec} = \text{expit}(\text{logit}(P_{1,rec}) + \text{lor}_{3,rec})$
P_{rel}	$P_{2,rel} = \text{expit}(\text{logit}(P_{1,rel}) + \text{lor}_{2,rel})$	$P_{3,rel} = \text{expit}(\text{logit}(P_{1,rel}) + \text{lor}_{3,rel})$

- We can use a loop over the number of treatments $n.treat$
- ```

for(i in 2:n.treat){
 p.rec[,i]<-expit(logit(p.rec[,1])+lor.rec[,i-1])
 p.rel[,i]<-expit(logit(p.rel[,1])+lor.rel[,i-1])
}

```

## Making it probabilistic - vectorise

| Parameter | CBT (Option 2)                                                           | Antidepressant (Option 3)                                                |
|-----------|--------------------------------------------------------------------------|--------------------------------------------------------------------------|
| $P_{rec}$ | $P_{2,rec} = \text{expit}(\text{logit}(P_{1,rec}) + \text{lor}_{2,rec})$ | $P_{3,rec} = \text{expit}(\text{logit}(P_{1,rec}) + \text{lor}_{3,rec})$ |
| $P_{rel}$ | $P_{2,rel} = \text{expit}(\text{logit}(P_{1,rel}) + \text{lor}_{2,rel})$ | $P_{3,rel} = \text{expit}(\text{logit}(P_{1,rel}) + \text{lor}_{3,rel})$ |

- Or we can vectorise, which is much faster than a loop
- ```

p.rec[,c(2:n.treat)]<-expit(logit(p.rec[,1])+lor.rec[,c(2:n.treat)-1])
p.rel[,c(2:n.treat)]<-expit(logit(p.rel[,1])+lor.rel[,c(2:n.treat)-1])
  
```
- The expit and logit functions work on vectors and matrices.
 - Can set n.treat to any number without having to duplicate code.

Formatting results

- Use `paste("string1", "string2")` function for string concatenation
- Use `round(x,digits=3)` for numeric formatting

```
format.results<-function(x,digits=2)
```

```
{
  paste(round(mean(x),digits=digits),"
        (",round(quantile(x,probs=0.025),digits=digits),"
        ",round(quantile(x,probs=0.975),digits=digits),")",sep="")
}
> c.rec<-rnorm(n=n.samples, mean=1000, sd=50)
> format.results(c.rec)
[1] "999.38 (901.73, 1095.85)"
>
```

Decision tree results

- Build a results matrix

```
results.matrix<-matrix(NA, nrow=4,ncol=n.treat)
```

- Name the rows and columns

```
rownames(results.matrix)<-c("Total costs", "Total QALYs", "Net Benefit", "Incremental NB")
```

```
colnames(results.matrix)<-t.names
```

- Then calculate summaries

```
for(i.treat in 1:n.treat)
```

```
{
  results.matrix["Total costs",i.treat]<-format.results(x=costs[,i.treat])
  results.matrix["Total QALYs",i.treat]<-format.results(x=effects[,i.treat])
  results.matrix["Net Benefit",i.treat]<-format.results(x=net.benefit[,i.treat])
  results.matrix["Incremental NB",i.treat]<-format.results(x=incremental.nb[,i.treat])
}
```

Exporting the results matrix to Excel

- Export as a csv

```
write.csv(results.matrix, file="depression.results.csv")
```

- Or as an Excel file

```
library(xlsx)
```

```
write.xlsx(results.matrix, file="depression.results.xlsx", sheetName="CEA results")
```

	No treatment	CBT	Antidepressant
Total costs	2458.08 (2216.38, 2692.91)	2678.9 (2424.37, 2937.03)	2366.58 (2087.97, 2621.49)
Total QALYs	20.09 (12.87, 27.59)	20.41 (13.54, 27.56)	20.59 (14.02, 27.52)
Net Benefit	549117.1)	548404.61)	548049.21)
Incremental NB	0 (0, 0)	6162.68 (-1978.38, 26095.58)	9996.67 (-2660.86, 36001.2)

So you can link back to Excel if you really can't resist.



19

And next?

- The model is available for you to try:
 - <https://github.com/Bogdasayen/Depression-toy-decision-tree-in-R>
- A full Markov cost-effectiveness model is also available:
 - <https://github.com/Bogdasayen/DOACs-AF-Economic-model>
- Bristol University will run a 2-day introductory course on R for Economic Evaluation.
 - Internal pilot in 2019, open externally in 2020.
- Devin will now show you what can be done once R is mastered...



20

Thank you!

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