
An overview of a suite of functions for CEA in \mathbb{R} using continuous-time multi-state modelling

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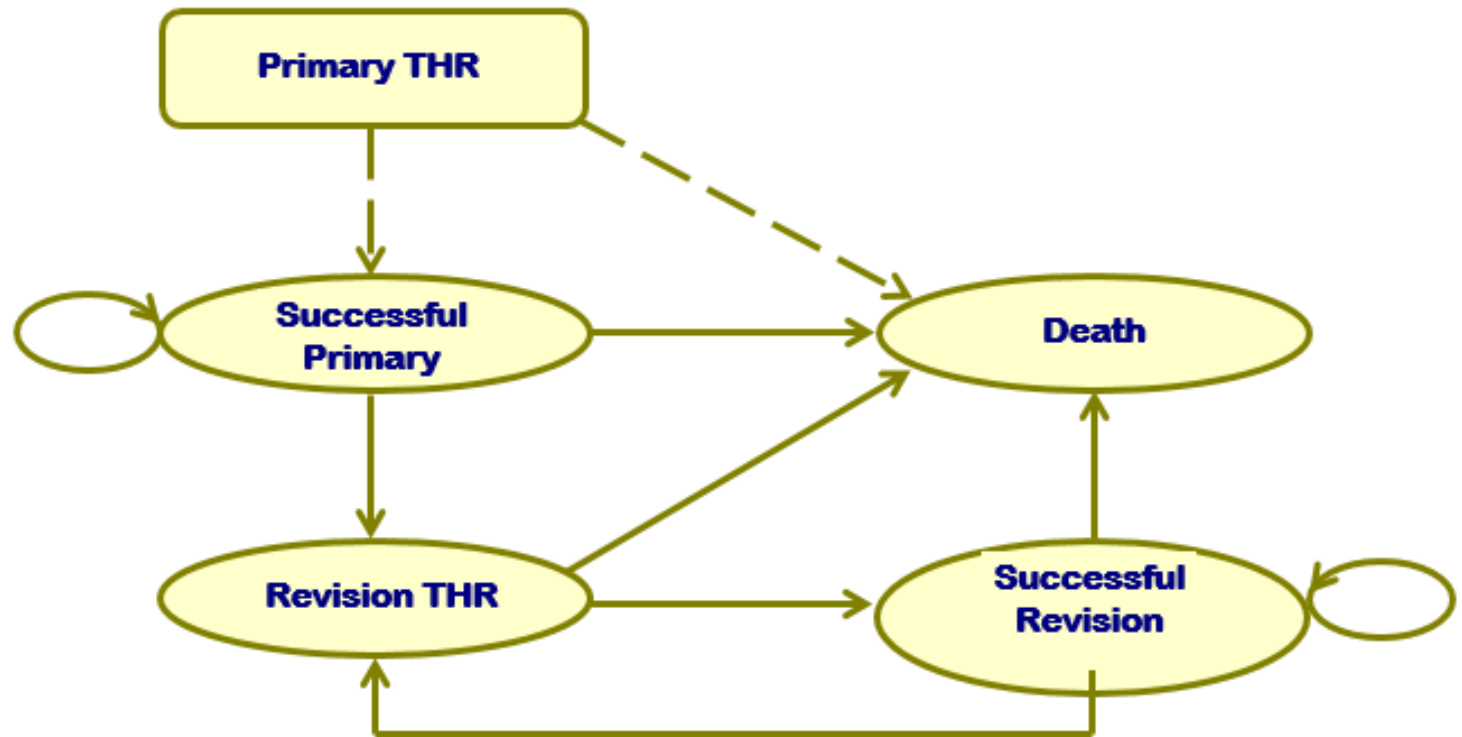
R for CEA Workshop, UCL

11th July 2018

Motivation

- Excel-based Markov modelling course gave the incentive to use R as an alternative
- Particular approach is based on `mstate` package in R
 - `mstate` uses IPD to build Cox models for each transition
 - `mstate` was adapted to use parametric distributions for the hazards: exponential, Weibull, Gompertz, log normal, log-logistic, generalised gamma
 - original motivation: extrapolation
 - another advantage: don't necessarily need IPD – just need to supply a cumulative hazard

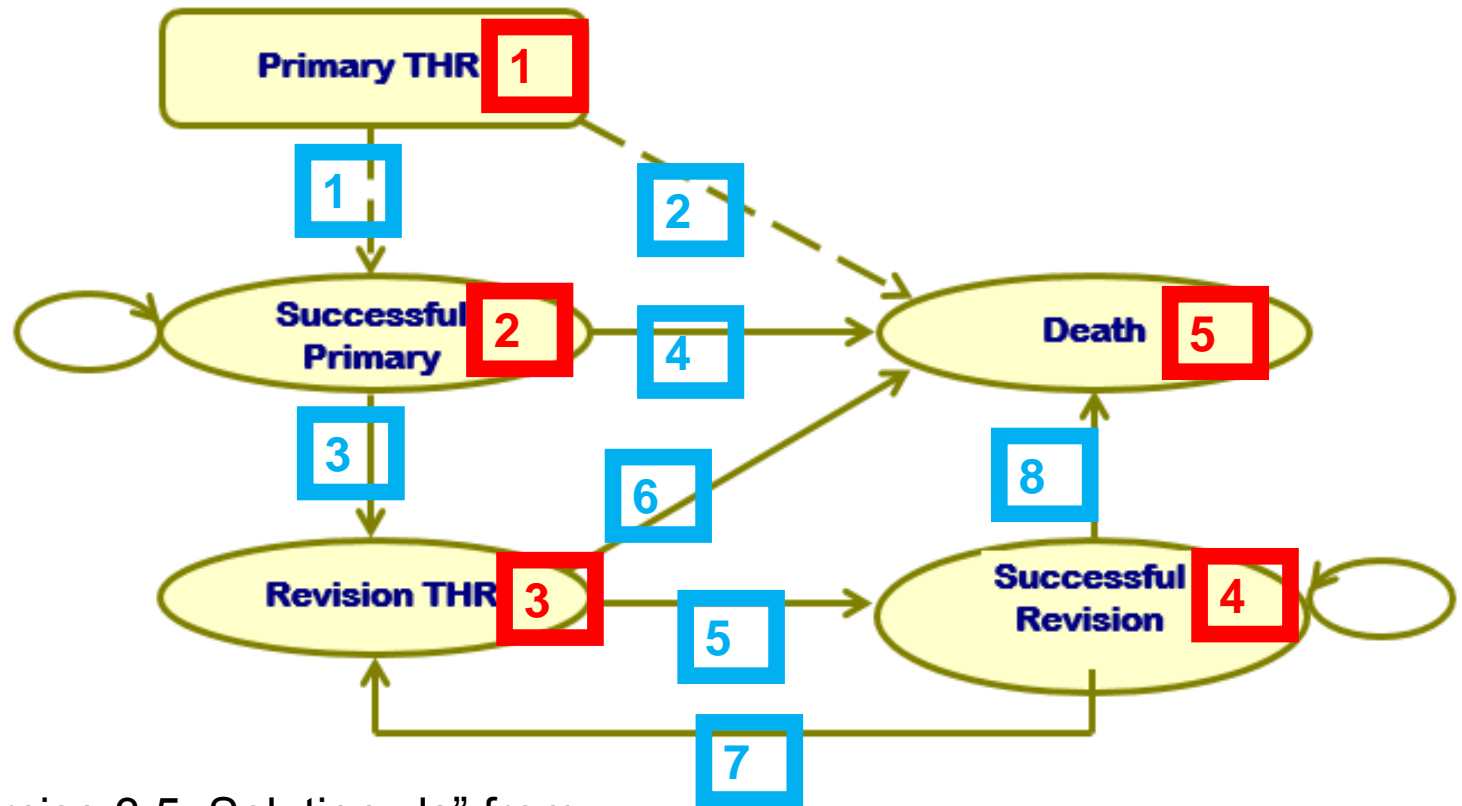
Hip fracture Markov model example



Source: “Exercise 3.5: Solution.xls” from

<https://www.gla.ac.uk/hehta/continuingprofessionaldevelopment/advancedmodellingmethods/#/downloads>

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State transition diagram R code

```
tmat <- transMat(x = list(c(2, 5), c(3,5),c(4,5),  
c(3,5), c()), names=c("Primary", "PriSuc",  
"Revision", "RevSuc","Death"))
```

```
tmat  
      to  
from   Primary PriSuc Revision RevSuc Death  
Primary      NA      1      NA      NA      2  
PriSuc      NA      NA      3      NA      4  
Revision    NA      NA      NA      5      6  
RevSuc      NA      NA      7      NA      8  
Death      NA      NA      NA      NA      NA
```

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```

tmat

to

from	Primary	PriSuc	Revision	RevSuc	Death
Primary	NA	1	NA	NA	2
PriSuc	NA	NA	3	NA	4
Revision	NA	NA	NA	5	6
RevSuc	NA	NA	7	NA	8
Death	NA	NA	NA	NA	NA

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tmat

to

from	Primary	PriSuc	Revision	RevSuc	Death
Primary	NA	1	NA	NA	2
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Revision	NA	NA	NA	5	6
RevSuc	NA	NA	7	NA	8
Death	NA	NA	NA	NA	NA

Alternative approach to relaxing the Markov property

Markov property - future states depend only on the present state and not on how it arrived in the present state

- Markov property can be formally tested by including in the model a covariate that represents history e.g. time in previous state
- If covariate is found to have a statistically significant effect there is evidence that the Markov property doesn't hold

Modelling progression → death time in previous state included as a covariate

Call:

```
coxph(formula = Surv(Tstart, Tstop, status) ~ treat +  
      prog_ty,  
      data = msmcancer3, method = "breslow")  
n= 254, number of events= 50
```

	coef	exp(coef)	se(coef)	z	Pr(> z)
treat	0.4416	1.5552	0.2938	1.503	0.13280
prog_ty	-0.8832	0.4135	0.3332	-2.651	0.00804

Markov and semi-Markov models

Markov models

- time measured from initial state regardless of state
- inherent Markov property
- predictions use Markov exact prediction formulae

Semi-Markov models

- time set back to zero every time patient enters a new state (clock-reset model)
- time depends on history so not Markov
- predictions use simulation sampling through available paths in the model

IPD – based functions: Markov or semi-Markov models

- `modelparam`
- `Markov` `semiMarkov`
- `visualMarkov` `visualsemiMarkov`
- `meanLY`
- `PSAprob`
- `PSAmeanLY` `PSAQALY`
- `CEplane`
- `CEAC`

modelparam function

```
modelparam(Markov=FALSE, covs="treat", trans  
num=3, dist="wei", data=msmcancer)
```

Covariate	W.mean	Coef	Exp(Coef)	se(Coef)	Wald p
treat	0.389	0.237	1.267	0.300	0.430
log(scale)		1.368		0.218	0.000
log(shape)		0.143		0.116	0.218
Events	45				
Total time at risk	192.69				
Max. log. likelihood	-109.46				
LR test statistic	0.62				
Degrees of freedom	1				
Overall p-value	0.432542				

Markov and semiMarkov functions

```
Markov(ntrans=3, ncovs=c(1,1,2),
      covs=rbind("covariate1", "covariate1",
                 c("covariate1", "covariate2")),
      coveval=rbind(0,0,c(0,1)),
      dist=cbind("wei", "wei", "wei"),
      dist2=cbind(NA, NA, NA),
      timeseq=seq(0,4,1/12),
      timeseq_ext=seq(49/12,15,1/12),
      data=msmcancer, trans=tmat)
```

visualMarkov and visualsemiMarkov functions

```
visualMarkov(nobjects=6,  
  objects=rbind(weiexactRFC, expexactRFC, gomexactRFC,  
  loglexactRFC, lognexactRFC, gamexactRFC),  
  objects2=rbind(weiexactRFC[[2]], expexactRFC[[2]],  
  gomexactRFC[[2]], loglexactRFC[[2]], lognexactRFC[[2]],  
  gamexactRFC[[2]]) ,state=1, instate=TRUE, absorb=1,  
  initialstate=TRUE,predfrom=2,  
  tteach=c(181,181, 181, 181, 181, 181),  
  ylab = "Probability of being progression-free",  
  xlab="Years since start of study",ylim=c(0,1),xlim=c(0,15),  
  lwd=2, col=rep("black",6),  
  lty=c("51","dotted","21", "longdash","twodash", "16"),
```

continued on next slide

visualMarkov and visualsemiMarkov functions

```
obsdata=RFCdata, CI=FALSE, observed="KM",  
KMtime=RFCdata$progdeath_ty, KMstatus=RFCdata$progdeath,  
ncr=2, legendpos="topright", legendncol=1, legendcex=1,  
  legendcurves=c("Kaplan-Meier", "Exponential", "Lognormal",  
  "Loglogistic", "Weibull", "Generalised gamma", "Gompertz"),  
  legendlty=c("solid", "dotted", "twodash", "longdash", "51", "16",  
  "21" ),  
  legendbty="n" , legendlwd=2, legendcol="black",  
  main="Probability of being progression-free",  
  cex.main=1.25)
```

meanLY function

```
meanLY (Markov=FALSE, object, state=1, instate=TRUE,  
        discounted=TRUE, dislyronwards=TRUE, rate=0.035)
```

	RFC	FC	Incremental
Mean Life Years	5.82	5.60	0.21
Mean Life Years Progression-free	3.30	2.56	0.74
Mean Life Years in Progression	2.52	3.04	-0.53
Mean QALYs	4.15	3.87	0.28
Mean QALYs Progression-free	2.64	2.05	0.59
Mean QALYs in Progression	1.51	1.83	-0.32

incorporating costs

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Mean Life Years	5.82	5.60	0.21
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Mean QALYs	4.15	3.87	0.28
Mean QALYs Progression-free	2.64	2.05	0.59
Mean QALYs in Progression	1.51	1.83	-0.32
Mean Total Cost	£25,917	£15,508	£10,408
Cost per Life Year Gained			£48,772
Cost per QALY Gained			£37,665

PSAprob function

```
PSAprob(ntrans=3, ncovs=c(1,1,2),
  covs=rbind("treat", "treat", c("treat", "lemedian")),
  coveval=rbind(0,0,c(0,0)),
  dist=cbind("wei", "wei", "wei"),
  dist2=cbind(NA, NA, NA),
  timeseq=seq(0,4,1/12),
  timeseq_ext=seq(49/12,15,1/12),
  data=msmcancer, trans=tmat,
  Markov=FALSE,
  nruns=1000, seedno=12345, M=100)
```

PSAmeanLY and PSAQALY functions

```
PSAmeanLY(object=PSASMSARFC, state=1, instate=TRUE,  
discounted=TRUE, rate=0.035)
```

```
set.seed(12345)
```

```
utility1=rbeta(1000, 800, 200)
```

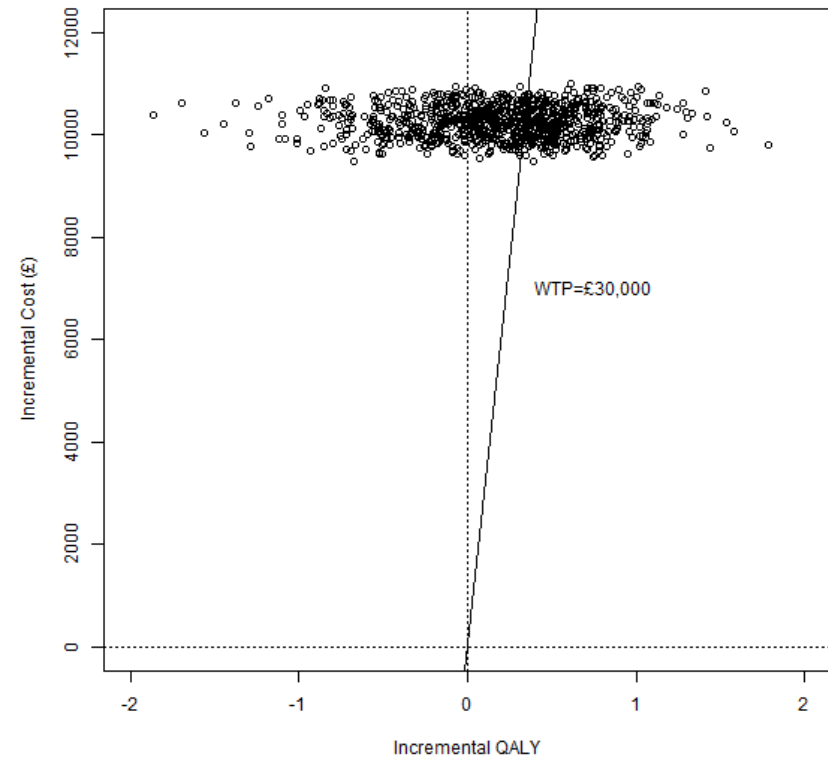
```
PSARFCQALYPFSdis<- PSAQALY(object=PSASMSARFC,  
utility=utility1, state=1, discounted=TRUE,  
dislyronwards=TRUE, rate=0.035)
```

```
mean(PSARFCQALYPFSdis)
```

then incorporate costs as probabilistic

CEplane function

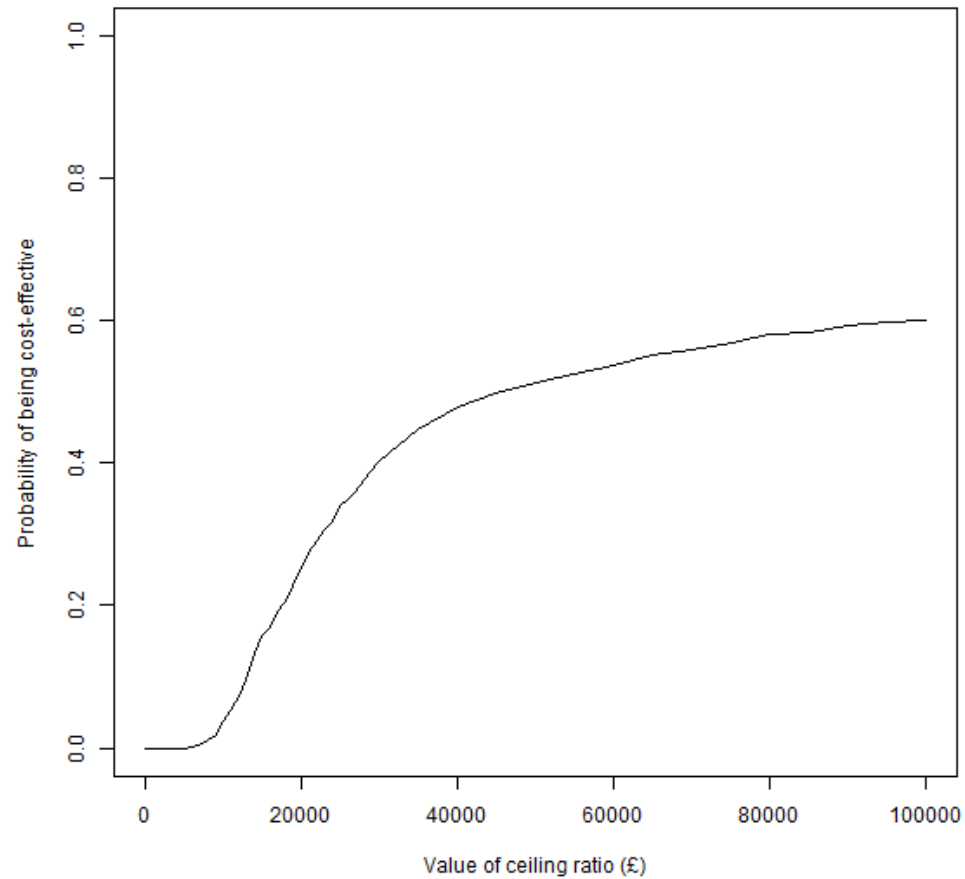
```
CEplane(x=incQALY, y=incCost, xlower=-2,  
xupper=2, ylower=0, yupper=20000, ICER=30000,  
text="ICER= £30,000")
```



CEAC function

```
CEAC(cRatiosim=c(seq(0,1000,100),
seq(1500,5000,500),seq(6000,30000,1000),
seq(35000,100000,5000)),nruns=1000,nruns2=1000
, xlower=0, xupper=100000, ylower=0, yupper=1,
QALY1=QALY_RFC_dis, QALY2=QALY_FC_dis,
cost1=total_cost_RFC_dis,
cost2=total_cost_FC_dis,
secondcurve=FALSE, QALY1_2=QALY_RFC_dis,
QALY2_2=QALY_FC_dis,
cost1_2=total_cost_RFC_dis,
cost2_2=total_cost_FC_dis))
```

CEAC



functions that can be used without IPD

Markov_noipd **and** semiMarkov_noipd

- allow previous model output and background mortality rates to be used to inform transition assumptions
- somewhat limited at the moment

Excel hip fracture model has been coded in R

- If interested please email me for my code:

claire.williams@bristol.ac.uk

Not included but discussed by others

- Previous speakers already discussed Vol analysis in \mathbb{R}
- Bobby and Iryna demonstrated shiny to create a more user-friendly front-end
- Looking forward: encourage more use of \mathbb{R} for health economic modelling

Acknowledgements

Financial support for this research was provided entirely by a doctoral training grant from the Medical Research Council in the United Kingdom (MR/J50032X/1).



The HTMR Collaboration and innovation in Difficult and Complex randomised controlled Trials In Invasive procedures (ConDuCT-II) hub provided support for this workshop



ConDuCT-II Hub

Reference

Williams, C., Lewsey, J. D., Briggs, A. H. , Mackay, D. F. (2017) Cost-effectiveness analysis in R using a multi-state modeling survival analysis framework: a tutorial. *Medical Decision Making*, 37:340-352.

doi:[10.1177/0272989X16651869](https://doi.org/10.1177/0272989X16651869)