

idem: Inference in Randomized Controlled Trials with Death and Missingness

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Introduction

In randomized studies involving severely ill patients, functional outcomes are often unobserved due to missed clinic visits, premature withdrawal or death. It is well known that if these unobserved functional outcomes are not handled properly, biased treatment comparisons can be produced.

R package **idem** implement a procedure for comparing treatments that is based on the composite endpoint of both the functional outcome and survival. The procedure considers missing data imputation with a sensitivity analysis strategy to handle the unobserved functional outcomes not due to death.

Data accepted by idem

In dataset accepted by **idem**, each row should represent a subject with treatment assignment, baseline covariates, baseline outcome, post-randomization outcomes and survival time.

The **idem** package provides dataset *abc* from *ABC* trial as an example data set.

```
head(abc);
```

```
##      AGE TRT SURV Y2 Y1
## 1 59.63   1  999 NA  NA
## 2 66.89   0  999 52  49
## 3 59.70   1    1 NA  NA
## 4 81.41   0   72 NA  NA
## 5 66.52   1  999 45  51
## 6 40.27   0   65 NA  NA
```

Basic setting

Parameters of most functions in **idem** are organized and passed by a list. These parameters include variable names in the dataset, endpoint specification, duration of the study, etc..

The function **chkPara** checks the specification in the list of parameters for errors:

```
err.lst.var <- list(trt="TRT", outcome=c("Y1", "Y2"),
                  y0=NULL, endfml="Y2", bounds=c(10,20),
                  duration=365);
```

```
chkPara(err.lst.var, abc);
```

```
## Model specification in not valid. Please check the following:
## ----No survival time specified
## ----Endpoint does not involve outcome
## ----Upper bound is bigger than some observed outcomes
```

```
lst.var <- list(trt="TRT", surv="SURV", outcome=c("Y1", "Y2"),
               y0=NULL, endp=c("Y2"),
               unitTime="days",
               trt.label = c("UC+SBT", "SAT+SBT"),
               cov=c("AGE"), endfml="Y2",
               duration=365, bounds=c(0,100));
```

```
chkPara(lst.var, abc);
```

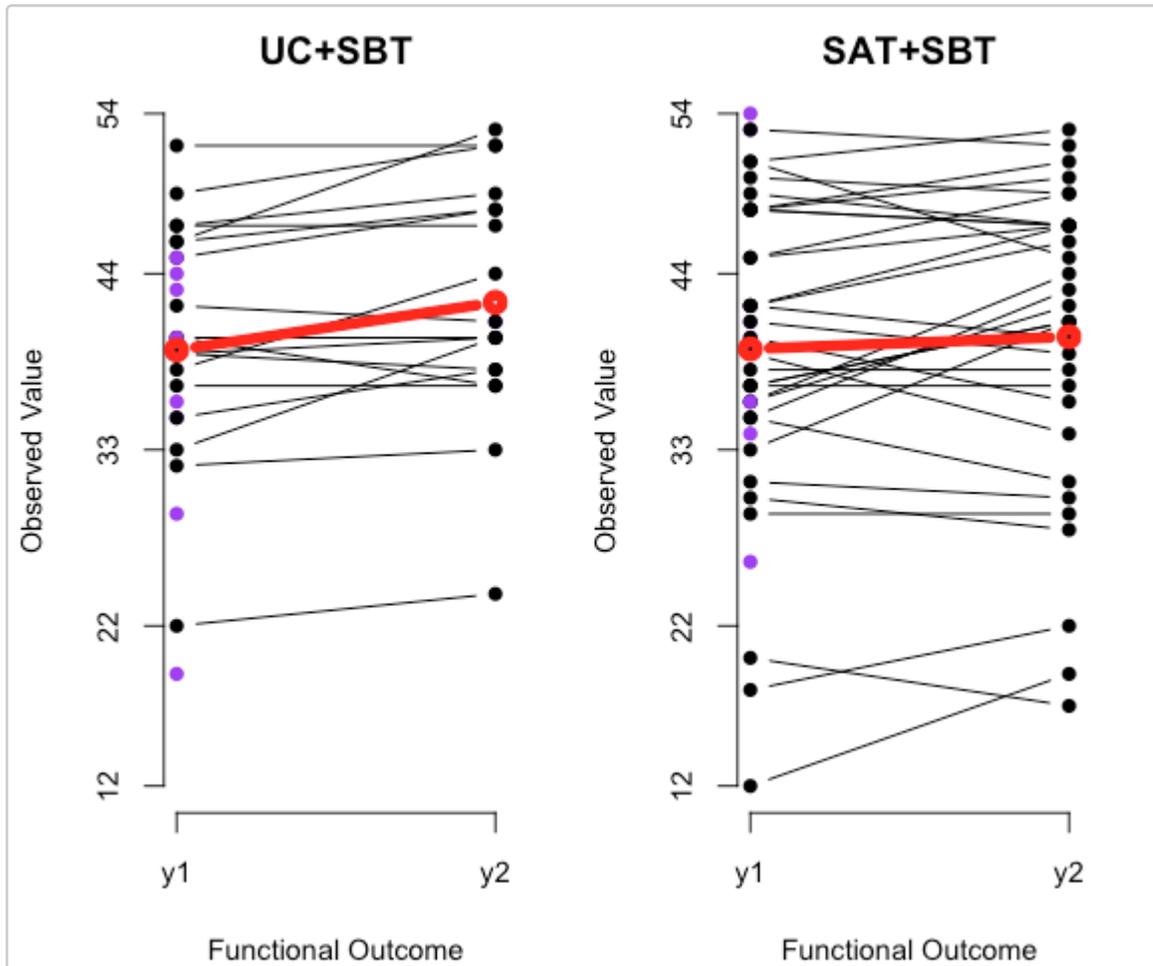
```
## No error found.
```

Data visualization

idem provides several functions for the visualization of the data.

Spaghetti plot for completers

```
plotCompleters(abc, lst.var);
```



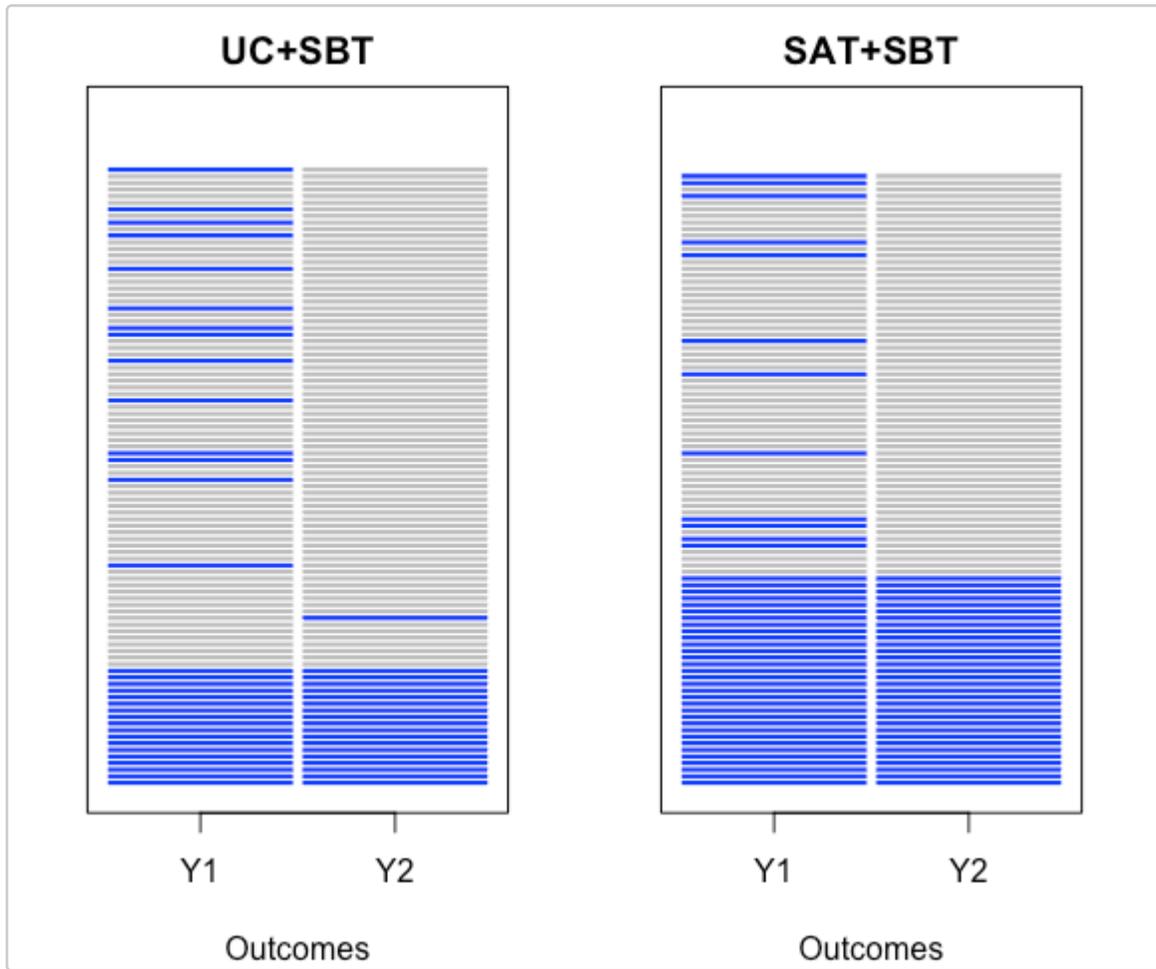
Missing pattern frequency table

```
get.mis.table(abc, 1st.var);
```

##	Y1	Y2	Control	Intervention
## Deaths on study	""	""	"58 (62%)"	"38 (41%)"
## S=1	"Observed"	"Observed"	"18 (19%)"	"32 (34%)"
## S=2	"Observed"	"Missing"	"8 (9%)"	"8 (9%)"
## S=3	"Missing"	"Observed"	"1 (1%)"	"0 (0%)"
## S=4	"Missing"	"Missing"	"9 (10%)"	"15 (16%)"
## Total	""	""	"94"	"93"

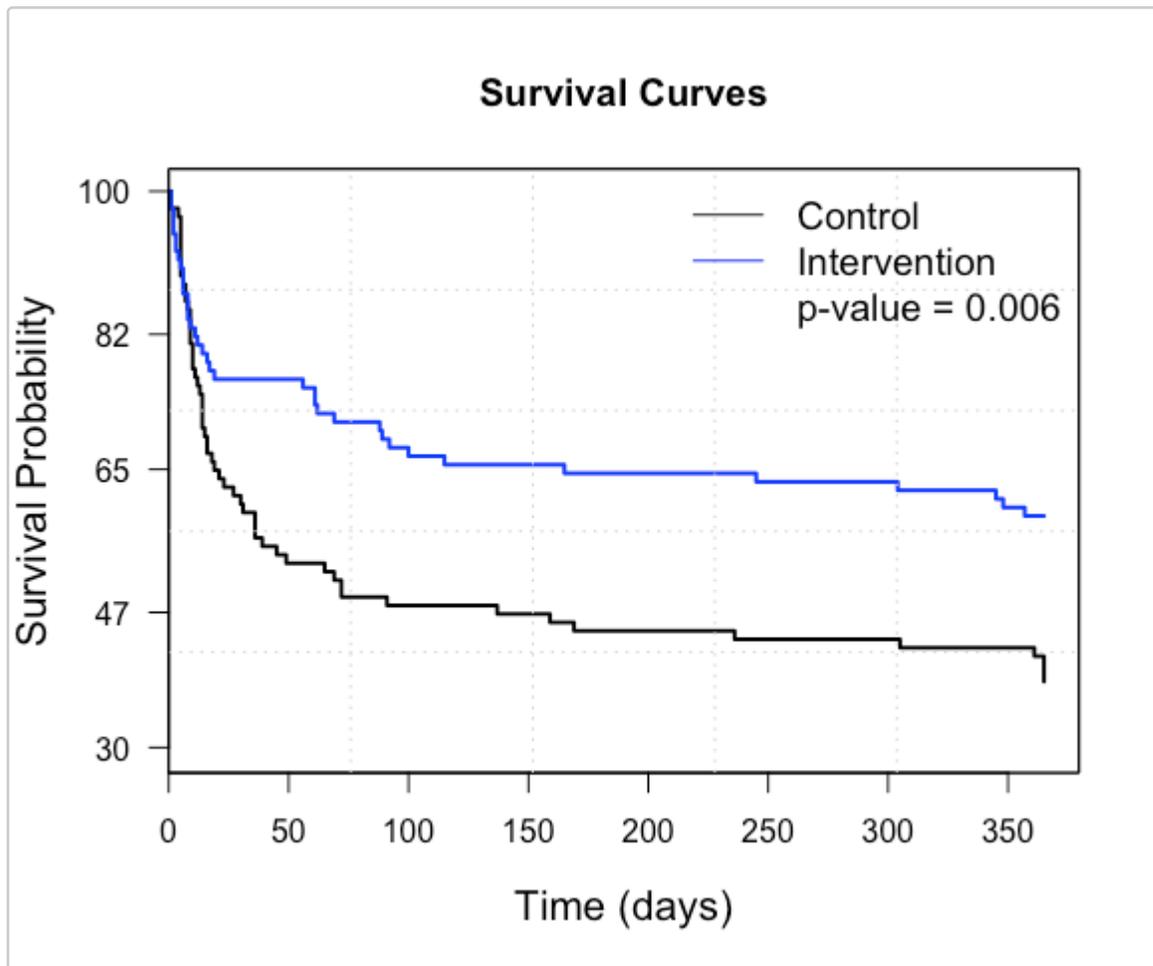
Missing pattern heatmap

```
plotMisPattern(abc, 1st.var);
```



Kaplan-Meier curves

```
plotSurv(abc, lst.var);
```



Missing data imputation

Model fitting

The first step in missing data imputation is to fit the imputation model to data observed from the completers, i.e. the subjects who were alive at the end of the study without missing data. The result has class name **IDEM.FIT**, which will be passed to imputation functions.

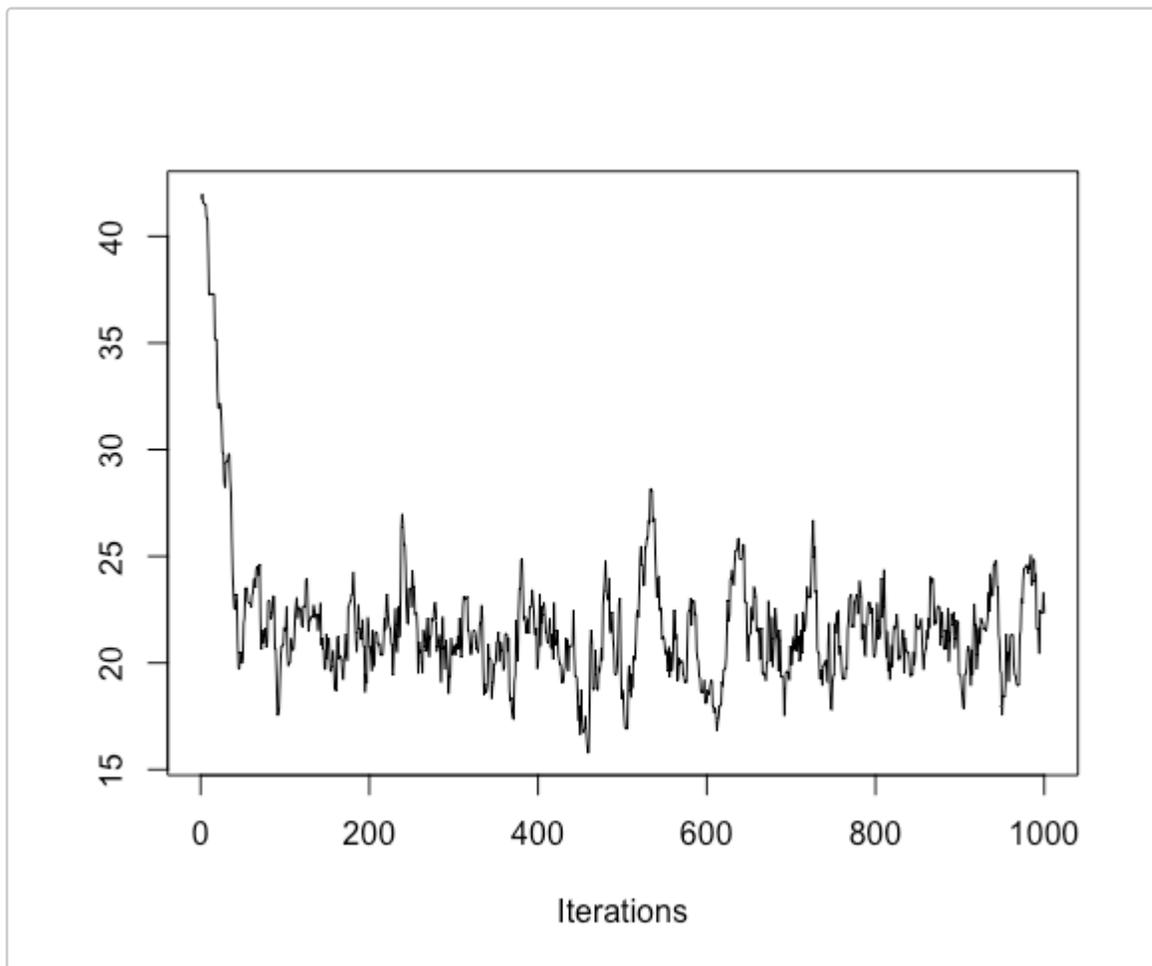
```
rst.fit <- fit.model(abc, lst.var);
```

Check convergence

The **p.scale** factor adjusts the mixing of the MCMC sampling for the imputation of missing values. It is suggested that the convergence of the MCMC chains for at least a small subset of the subjects should be checked first. This can be done by the **get.imp.all** function by setting **trace.n** to be a non-zero number.

```
rst.mixing <- get.imp.all(abc, rst.fit, lst.var, deltas=0,
```

```
trace.n=1, normal=TRUE, iter=1000,  
p.scale=10);  
  
## [1] 1  
  
rst.chain <- list();  
for (i in 1:ncol(rst.mixing$mcmc[[1]])) {  
  rst.chain[[i]] <- rst.mixing$mcmc[[1]][,i,drop=FALSE];  
}  
coda::traceplot(rst.chain);
```



Imputation

The following code shows how to use `get.imp.all` to get the imputed complete datasets under benchmark assumption `delta=0` and for sensitivity analysis. We use **300** iterations to reduce the computation time.

```
rst.imp <- get.imp.all(abc, rst.fit, lst.var, deltas=c(-0.25,0,0.25),  
normal=TRUE, iter=300, n.imp=2, thin=10,
```

```
p.scale=10);
```

The following results show the completed datasets:

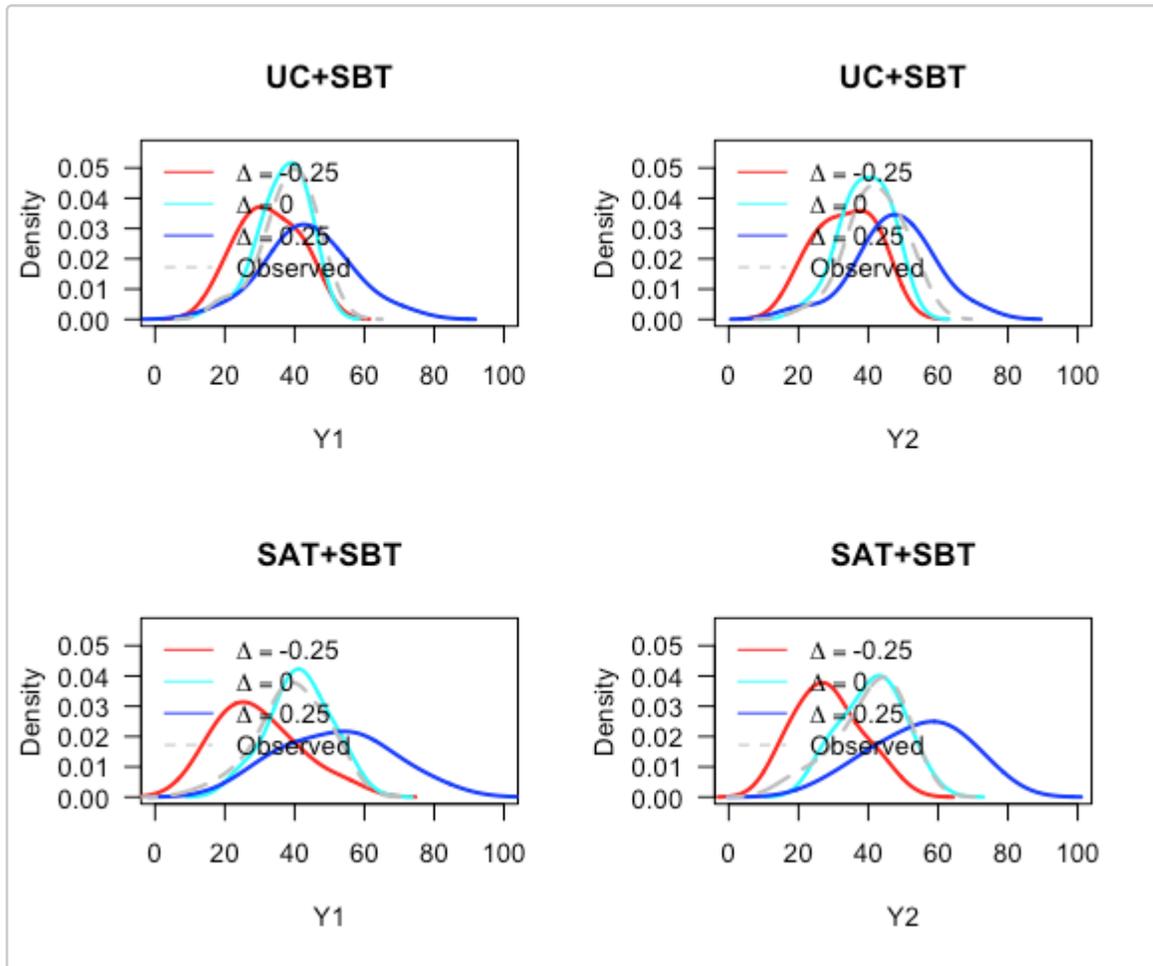
```
tail(rst.imp, n=10);
```

##	ID	DELTA	IMP	AGE	TRT	SURV	Y2	Y1	ORGY1	ORGY2	ENDP	
##	1852	186	0.00	1	67.06	0	999	41.56661	36	36	NA	41.56661
##	1853	186	0.00	2	67.06	0	999	32.64299	36	36	NA	32.64299
##	1854	186	0.25	1	67.06	0	999	39.48108	36	36	NA	39.48108
##	1855	186	0.25	2	67.06	0	999	38.66370	36	36	NA	38.66370
##	187	187	-0.25	1	66.12	1	999	24.90369	26	26	NA	24.90369
##	1871	187	-0.25	2	66.12	1	999	25.19095	26	26	NA	25.19095
##	1872	187	0.00	1	66.12	1	999	29.77881	26	26	NA	29.77881
##	1873	187	0.00	2	66.12	1	999	29.12097	26	26	NA	29.12097
##	1874	187	0.25	1	66.12	1	999	31.90955	26	26	NA	31.90955
##	1875	187	0.25	2	66.12	1	999	24.47117	26	26	NA	24.47117

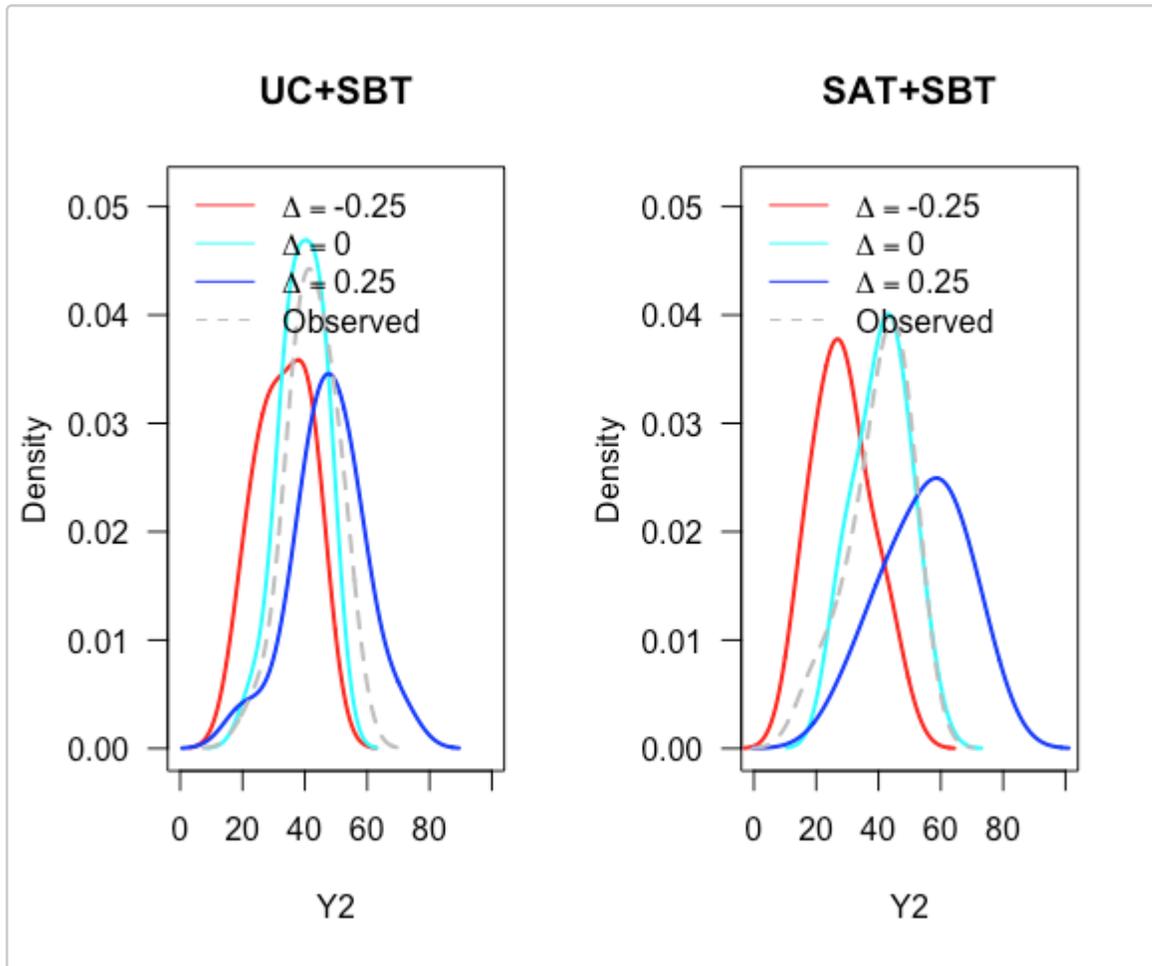
Plot density of the imputed data

Function **plotImputed** plots the densities of the imputed outcomes and the imputed functional endpoint.

```
plotImputed(rst.imp, lst.var, deltas=c(-0.25,0,0.25), xlim=c(0,100), endp=FALSE);
```



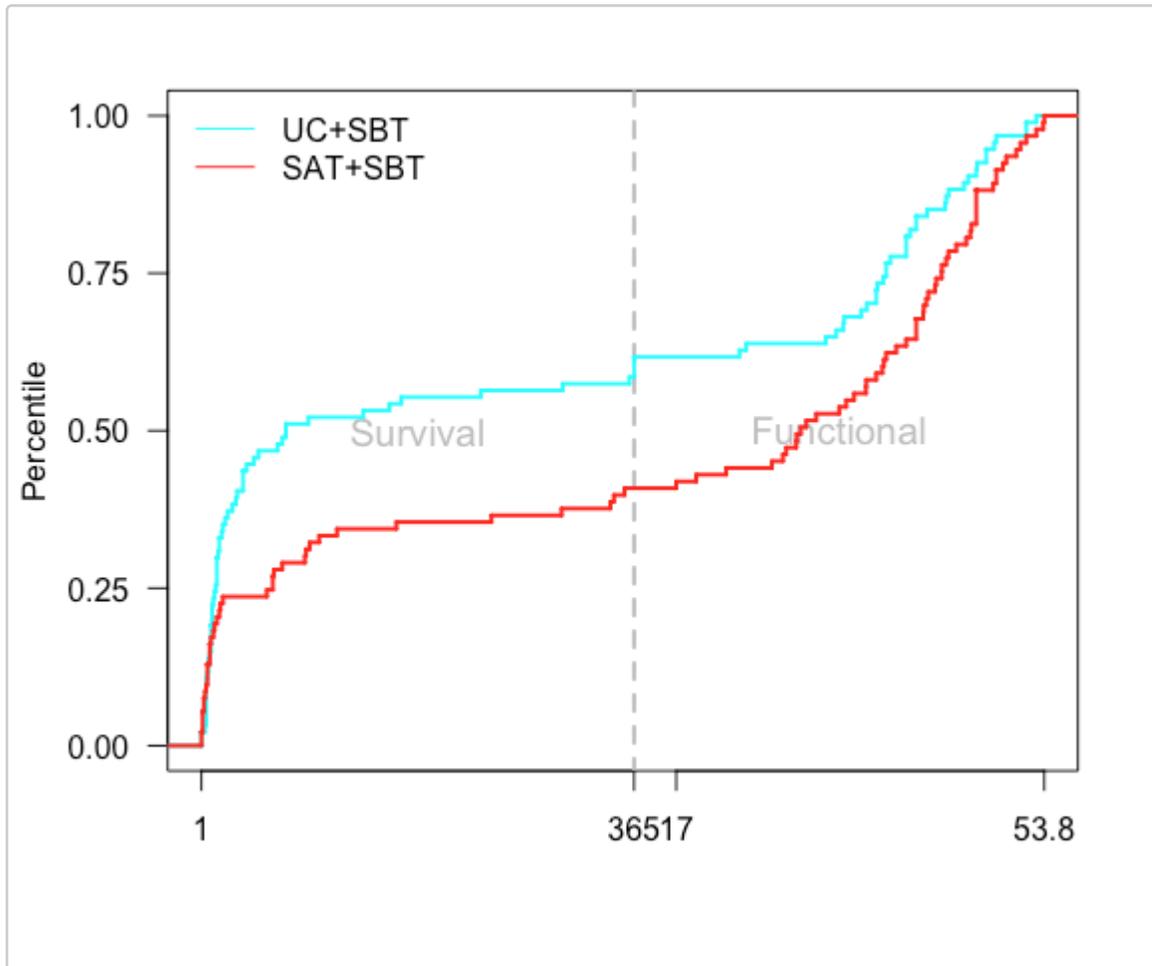
```
plotImputed(rst.imp, lst.var, deltas=c(-0.25,0,0.25), xlim=c(0,100), endp=TRUE);
```



Plot the cumulative distribution of the composite endpoint

Function **plotComposite** generates the treatment-specific cumulative distribution functions of the composite endpoint, where the values of the composite endpoint are labeled according to the survival time and functional endpoint among survivors.

```
plotComposite(rst.imp, lst.var, delta=0);
```



Estimation of θ and quantiles

Given a complete dataset with imputed outcomes, **idem** estimates treatment effect and quantiles of the composite endpoint using function **get.theta.quantiles**:

```
rst.est <- get.theta.quantiles(rst.imp, lst.var, quantiles=c(0.25,0.5,0.75));
print(rst.est$theta);
```

```
##   Delta0 Delta1      Theta
## 1  -0.25  -0.25 -0.16815374
## 2   0.00  -0.25 -0.13532372
## 3   0.25  -0.25 -0.09460078
## 4  -0.25   0.00 -0.23713109
## 5   0.00   0.00 -0.20327156
## 6   0.25   0.00 -0.14607641
## 7  -0.25   0.25 -0.28506063
## 8   0.00   0.25 -0.25966598
## 9   0.25   0.25 -0.21150766
```

```
print(rst.est$quantiles);
```

```
##   Delta TRT   Q   Quant
## 1 -0.25  0 0.25 -1.00000
## 2 -0.25  0 0.50 -1.00000
## 3 -0.25  0 0.75 37.00000
## 4 -0.25  1 0.25 -1.00000
## 5 -0.25  1 0.50 22.01691
## 6 -0.25  1 0.75 39.89199
## 7  0.00  0 0.25 -1.00000
## 8  0.00  0 0.50 -1.00000
## 9  0.00  0 0.75 37.88017
##10  0.00  1 0.25 -1.00000
##11  0.00  1 0.50 29.56049
##12  0.00  1 0.75 43.86520
##13  0.25  0 0.25 -1.00000
##14  0.25  0 0.50 -1.00000
##15  0.25  0 0.75 40.50000
##16  0.25  1 0.25 -1.00000
##17  0.25  1 0.50 31.57008
##18  0.25  1 0.75 47.00000
```

Bootstrap analysis

idem evaluates the uncertainty of the estimated θ and quantiles by bootstrap analysis.

For illustration, we run **10** bootstrap samples by the following code:

```
rst.boot <- get.bs.all(n.boot = 10,
                      n.cores = 5,
                      data.all = abc,
                      lst.var = lst.var,
                      deltas = c(-0.25, 0, 0.25),
                      quantiles = c(0.25, 0.5, 0.75),
                      normal=TRUE, iter=300,
                      n.imp=2, thin=10,
                      p.scale=10);
```

Hypothesis testing

Hypothesis testing results and the confidence intervals of and quantiles of the composite endpoint are obtained by summarizing the results from the bootstrap analysis and the analysis on the original dataset:

```
rst.final <- get.overall.rst(rst.est, rst.boot);
```

```

print(rst.final);

## $theta
##   Delta0 Delta1      Theta      SD      PValue
## 1  -0.25  -0.25 -0.16815374 0.07973151 3.494460e-02
## 2   0.00  -0.25 -0.13532372 0.05970093 2.340893e-02
## 3   0.25  -0.25 -0.09460078 0.05357365 7.742805e-02
## 4  -0.25   0.00 -0.23713109 0.07796869 2.355096e-03
## 5   0.00   0.00 -0.20327156 0.05951428 6.366296e-04
## 6   0.25   0.00 -0.14607641 0.05060692 3.895638e-03
## 7  -0.25   0.25 -0.28506063 0.07748273 2.341306e-04
## 8   0.00   0.25 -0.25966598 0.06251603 3.272986e-05
## 9   0.25   0.25 -0.21150766 0.05516525 1.260381e-04
##
## $quantiles
##   Delta TRT    Q   Quant      LB      UB
## 1  -0.25   0 0.25 -1.00000 -0.3090797 -0.072823725
## 2  -0.25   0 0.50 -1.00000 -0.2183082 -0.040265385
## 3  -0.25   0 0.75 37.00000 -0.1567862 -0.002144818
## 4  -0.25   1 0.25 -1.00000 -0.3950355 -0.158856669
## 5  -0.25   1 0.50 22.01691 -0.3032487 -0.117221460
## 6  -0.25   1 0.75 39.89199 -0.2183596 -0.070046900
## 7   0.00   0 0.25 -1.00000 -0.4376201 -0.207232327
## 8   0.00   0 0.50 -1.00000 -0.3711622 -0.189044269
## 9   0.00   0 0.75 37.88017 -0.3077070 -0.153085678
## 10  0.00   1 0.25 -1.00000 -0.3090797 -0.072823725
## 11  0.00   1 0.50 29.56049 -0.2183082 -0.040265385
## 12  0.00   1 0.75 43.86520 -0.1567862 -0.002144818
## 13  0.25   0 0.25 -1.00000 -0.3950355 -0.158856669
## 14  0.25   0 0.50 -1.00000 -0.3032487 -0.117221460
## 15  0.25   0 0.75 40.50000 -0.2183596 -0.070046900
## 16  0.25   1 0.25 -1.00000 -0.4376201 -0.207232327
## 17  0.25   1 0.50 31.57008 -0.3711622 -0.189044269
## 18  0.25   1 0.75 47.00000 -0.3077070 -0.153085678
##
## attr("class")
## [1] "IDEM.TEST"

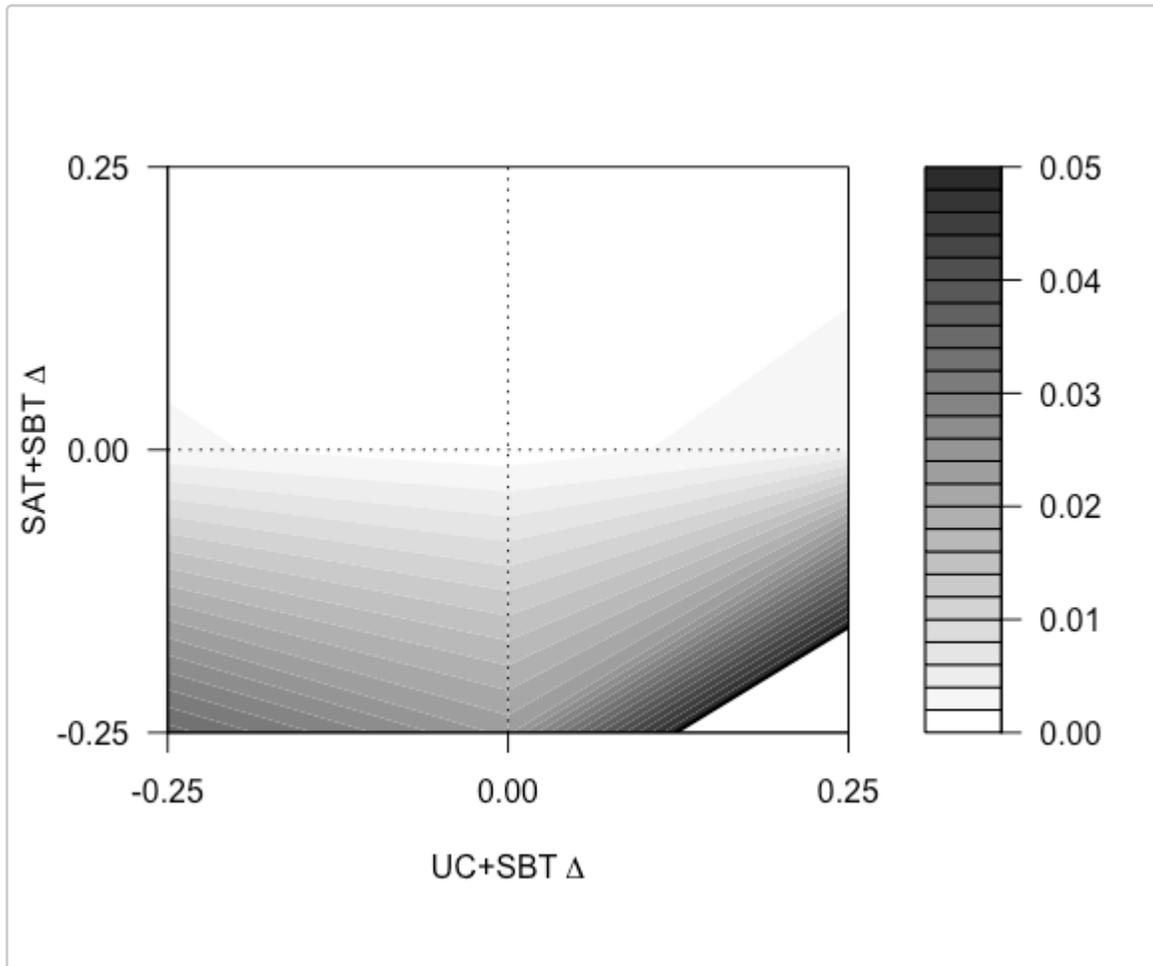
```

A contour plot of p-values in the sensitivity analysis results can be generated by `plotContour`:

```

plotContour(rst.final, lst.var, nlevels = 30,
            con.v=0.05, zlim=c(0, 0.05), main="");

```



```
##           [,1]      [,2]      [,3]
## [1,] 0.03494460 0.0023550963 2.341306e-04
## [2,] 0.02340893 0.0006366296 3.272986e-05
## [3,] 0.07742805 0.0038956375 1.260381e-04
```