The MortalitySmooth-Package: Additional Examples

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```
library(MortalitySmooth)

## Loading required package: svcm

## Loading required package: Matrix

## Loading required package: splines

## Loading required package: lattice
```

In this document, I collected additional examples which would have take too long for standard package examples. For more details on the methods behind, please check on:

```
citation("MortalitySmooth")
```

1 Examples in one-dimension

1.1 Including Extra-Poisson variation

This first example takes the documentation from Mort1Dsmooth() and shows the difference when an additional overdispersion parameter is included in the estimation procedure.

Directly from the examples in Mort1Dsmooth(), we select some data and then smooth them optimizing the smoothing parameter by a BIC:

Then we check the presence of overdispersion by looking at:

```
fitBIC$psi2
## [1] 12.34
```

which is quite larger than 1 and therefore we dhould account for such extra-Poisson variation in searching the optimal smoothing parameter. This can be done by setting the argument overdispersion to TRUE:

The difference in the selected λ gives an idea of the influence of such procedure:

```
fitBIC$lambda;fitBICover$lambda
## [1] 316.2
## [1] 3162
```

i.e. in presence of overdispersion we tend to get smoother outcomes. Let's see the difference in a plot (Figure 1):

```
plot(fitBICover)
lines(years, fitBIC$logmortality, col=4, lwd=2, lty=2)
```

1.2 Interpolating/Extrapolating using dummy data

Thought it would be more efficient and elegant to interpolate and extrapolate fitted values by means of predict(), here we show how to do using solely the main function Mort1Dsmooth() and suitable dummy data.

Taking the previous datasets, we assume the absence of data between 1969 and 1989 by adding NA in the vector of exposures:

```
exposure.int <- exposure
exposure.int[20:40] <- NA</pre>
```

A first attempt would be to directly fit using the new exposures, but a clear error message will be produced.

The proper way is to set up a suitable vector of weights which will inform the main function that estimation between 1969 and 1989 have zero-weight:

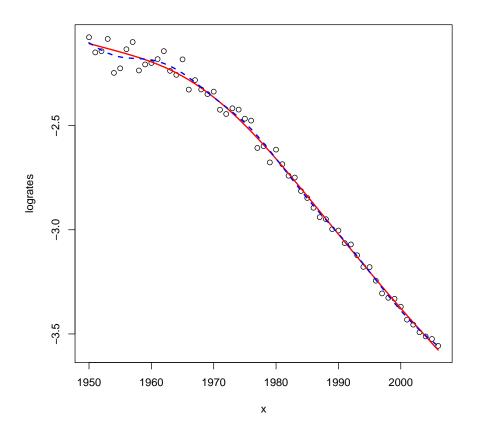


Figure 1: Actual and fitted log-mortality with and without accounting for extra-Poisson variation. Japanese women age 80 in years 1950-2006

Note that the function will produce a warning inform the user about the interpolation.

A plot will illustrate the effect of interpolating data (Figure 2):

```
plot(fit1Dint)
```

In the next example we illustrate how to extrapolate mortality data directly by MortlDsmooth() and with the means of proper weights and augmented data. Also in this case it would be simpler to use predict(), but in the following it will be easier to grasp the concept behind the procedure.

First we augment the vector of data:

```
years.ext <- seq(years[1], years[length(years)]+20)
exposure.ext <- c(exposure, rep(NA, 20))
death.ext <- c(death, rep(NA, 20))</pre>
```

Then we create a vector of weights in which we have ones in the observed years and zeros in the forecast ones:

```
w.ext <- c(rep(1, length(years)), rep(0, 20))
```

Then we can easily fit the model with these new data using the optimized smoothing parameter from fit1Dover:

Figure 3 shows the outcomes.

2 Examples in two-dimensions

2.1 Including Extra-Poisson variation

In the next example we will show the effect of including an overdispersion parameter in the searching of the optimal smoothing parameters in a 2D setting.

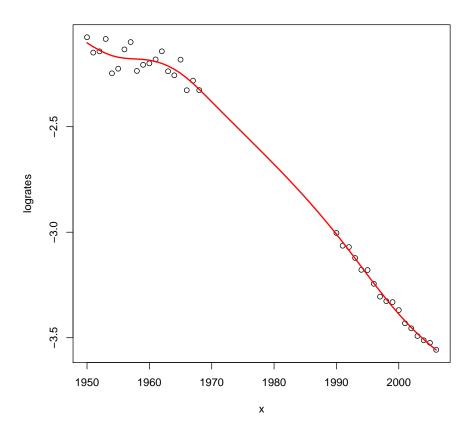


Figure 2: Actual and fitted log-mortality with interpolation between 1969 and 1989. Japanese women age 80 in years 1950-2006.

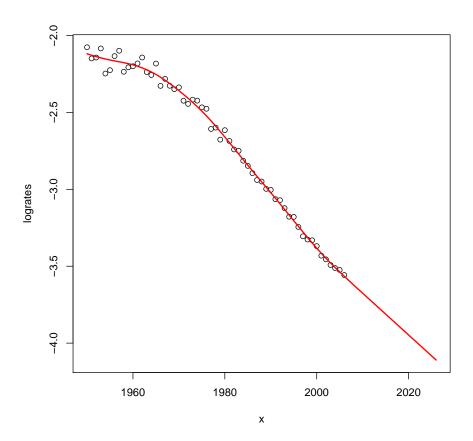


Figure 3: Actual, fitted and forecast log-mortality. Japanese women age 80 in observed years 1950-2006 and forecast years 2007-2026.

First we take data and default fit from the documentation in Mort2Dsmooth():

Then we check the estimated overdispersion parameter:

```
fitBIC$psi2
## [1] 1.309
```

which seems larger than 1. Therefore we set the argument ${\tt overdispersion}$ equal to TRUE:

The difference in the smoothing parameters is clear especially in the year direction:

```
fitBIC$lambdas

## [1] 1000.0 316.2

fitBICover$lambdas

## [1] 316.2 3162.3
```

2.2 Interpolating/Extrapolating using dummy data

Here we follow the same procedure presented in the one-dimensional setting, generalizing over a second domain.

Using the previous data, we assume the absence of data between age 69 and 79 by inserting NA in the matrix of exposures. Then we create a suitable matrix of weights and we use the main function Mort2Dsmooth(), plotting the fitted logrates:

Outcomes are given in Figure 4.

An additional example in 2D assume the lost of 90% of the mortality data and the interpolation over age and time of the complete mortality surface.

First we create a matrix of weights all equal to 1 in which we randomly assign zero values to about 90% of the cells. Then we just add this matrix in the argument W within the main function Mort2Dsmooth(). Outcomes are presented in Figure 5.

Likewise in 1D, we extrapolate our data by augmenting the data (matrices now) over the year domain and creating a suitable matrix of weights with zeros in the forecast years.

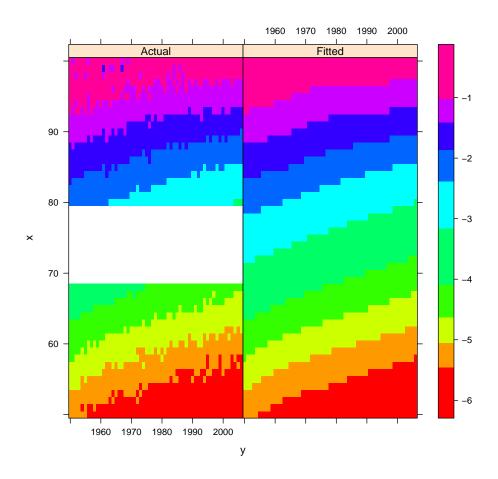


Figure 4: Actual and fitted log-mortality with interpolation between age 69 and 89. Swedish women from 50 to 100 in years 1950-2006.

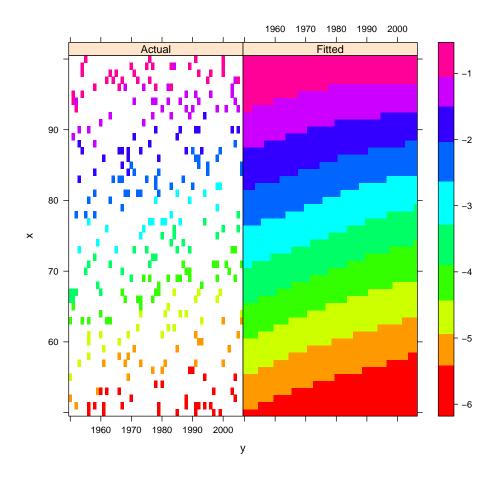


Figure 5: Actual and fitted log-mortality suing only random 10% of the available information. Swedish women from 50 to 100 in years 1950-2006.

plot(fit2Dext)

Outcomes are shown in Figure 6.

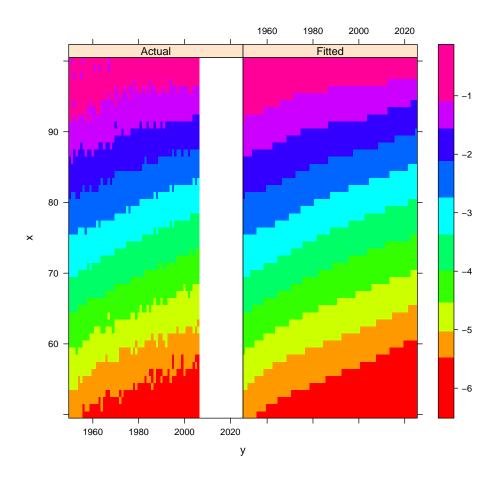


Figure 6: Actual, fitted and forecast log-mortality. Swedish women from 50 to 100 in observed years 1950-2006 and forecast years 2007-2025.