

# MswM examples

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## Abstract

Two examples are described to illustrate the use of the `MswM` package. First, a simulated dataset is modeled in detail. Next, Markov Switching Models are fitted to a real dataset with a discrete response variable. The main methods and graphical representations are used to validate different approaches to model these datasets.

## 1 Simulated Example

The `example` data is a simulated data set to show how `msmFit` can detect the presence of two different regimes: one in which the response variable is highly correlated and other in which the response only depends on an exogenous variable  $x$ . The autocorrelated observations are in the intervals 1 to 100, 151 to 180 and 251 to 300. The real models for each regime are:

$$y_t = \begin{cases} 8 + 2x_t + \varepsilon_t^{(1)} & \varepsilon_t^{(1)} \sim N(0, 1) & t = 101 : 150, 181 : 250 \\ 1 + 0.9y_{t-1} + \varepsilon_t^{(2)} & \varepsilon_t^{(2)} \sim N(0, 0.5) & t = 1 : 100, 151 : 180, 251 : 300 \end{cases}$$

```
> data(example)
```

The plot in Fig.1 shows that in the intervals where does not exist autocorrelation the response variable  $y$  has a similar behaviour as the covariant  $x$ . A linear model is fitted to study how the covariate  $x$  explains the variable response  $y$ .

```
> mod=lm(y~x, example)
> summary(mod)
```

Call:

```
lm(formula = y ~ x, data = example)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.8998	-0.8429	-0.0427	0.7420	4.0337

```
> plot(ts(example))
```

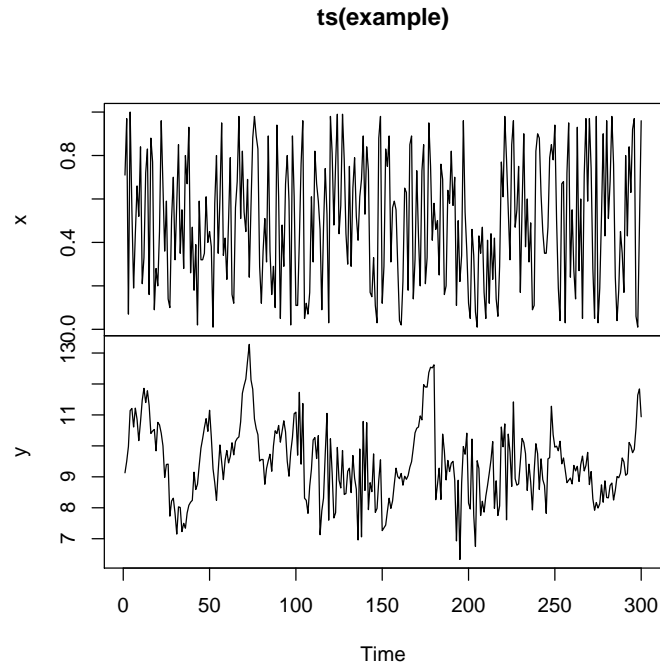


Figure 1: Simulated data. The y variable is the response variable and there are two periods in which this depends on the x covariate

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	9.0486	0.1398	64.709	< 2e-16 ***
x	0.8235	0.2423	3.398	0.00077 ***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.208 on 298 degrees of freedom

Multiple R-squared: 0.03731, Adjusted R-squared: 0.03408

F-statistic: 11.55 on 1 and 298 DF, p-value: 0.0007701

The covariate is really significant but the data behaviour is very bad explained by the model. The plot of the linear model residuals in Fig.1 indicates that their autocorrelation is significant. The diagnostics plots for the residuals (Fig.2) confirm that they does not seem to be white noise and that they have autocorrelation. Next, a Autoregressive Markov Switching Model (MSM-AR) is fitted to the data. The order for the autoregressive part is set to one. In order to indicate that all the parameters can be different in both periods, the switch-

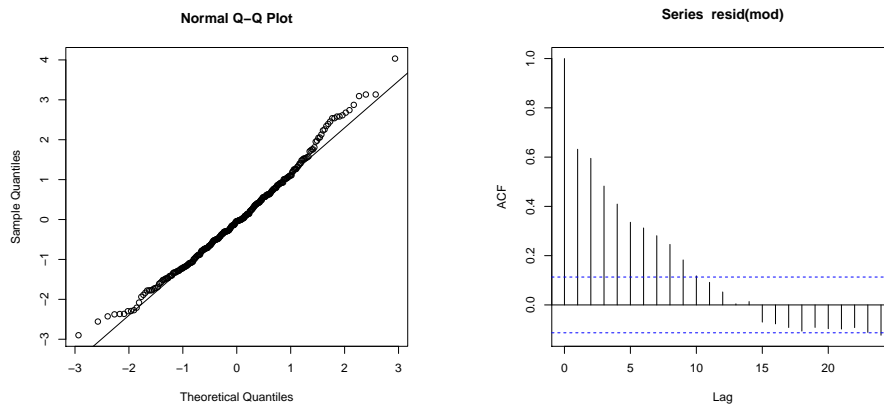


Figure 2: Normal Probability plot and Autocorrelation Function of the residuals from the linear model

ing parameter (`sw`) is set to a vector with four components with value equal to `TRUE`. The last value when fitting a linear model is referred to the residual standard deviation. There are some options to control the estimation process, like a logical parameter to indicate whether parallelization of the process is done or not.

```
> mod.mswm=msmFit(mod,k=2,p=1,sw=c(T,T,T,T),control=list(parallel=F))
> summary(mod.mswm)
```

### Markov Switching Model

Call: `msmFit(object = mod, k = 2, sw = c(T, T, T, T), p = 1, control = list(parallel = F))`

```
      AIC      BIC    logLik
637.0736 693.479 -312.5368
```

Coefficients:

Regime 1

-----

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)(S)	0.8417	0.3025	2.7825	0.005394	**
x(S)	-0.0533	0.1340	-0.3978	0.690778	
y_1(S)	0.9208	0.0306	30.0915	< 2.2e-16	***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5034675

Multiple R-squared: 0.8375

Standardized Residuals:

	Min	Q1	Med	Q3	Max
	-1.5153666657	-0.0906543311	0.0001873641	0.1656717256	1.2020898986

Regime 2

-----

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)(S)	8.6393	0.7244	11.9261	< 2.2e-16 ***
x(S)	1.8771	0.3107	6.0415	1.527e-09 ***
y_1(S)	-0.0569	0.0797	-0.7139	0.4753

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9339683

Multiple R-squared: 0.2408

Standardized Residuals:

	Min	Q1	Med	Q3	Max
	-2.31102193	-0.03317756	0.01034139	0.04509105	2.85245598

Transition probabilities:

	Regime 1	Regime 2
Regime 1	0.98499728	0.02290884
Regime 2	0.01500272	0.97709116

The model `mod.mswm` has a regime where the covariant `x` is very significant and in the other regime the autocorrelation variable is very significant too. In both, the R-squared have high values. Finally, the transition probabilities matrix has high values which indicate that is difficult to change from on regime to the other. The model detect perfectly the periods of each state. The residuals look like to be white noise and they fit to the Normal Distribution. Moreover, the autocorrelation has disappeared.

```
> plotProb(mod.mswm, which=1)
```

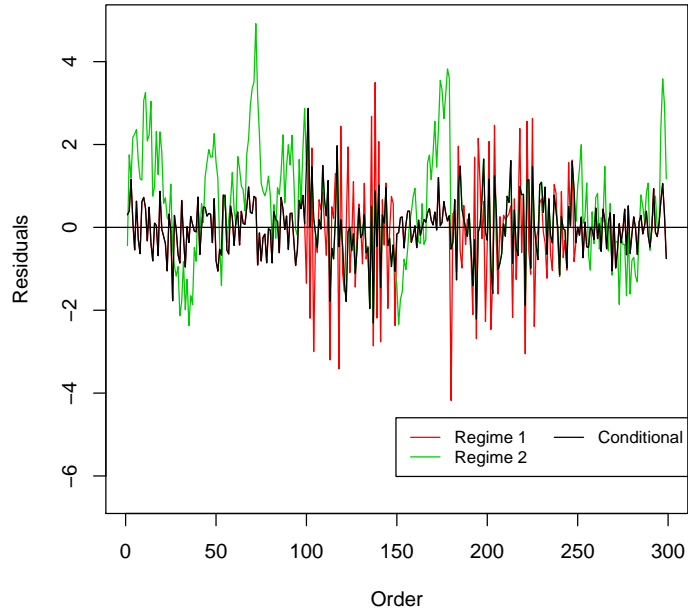


Figure 3: Residuals form the Autoregressive MSM model

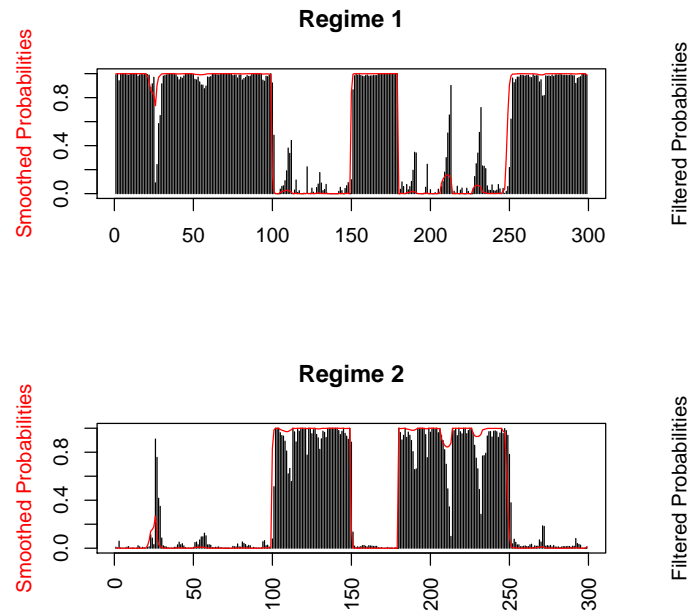


Figure 5: Filtered and Smoothed Probabilities for both regimes in the MSM-AR model

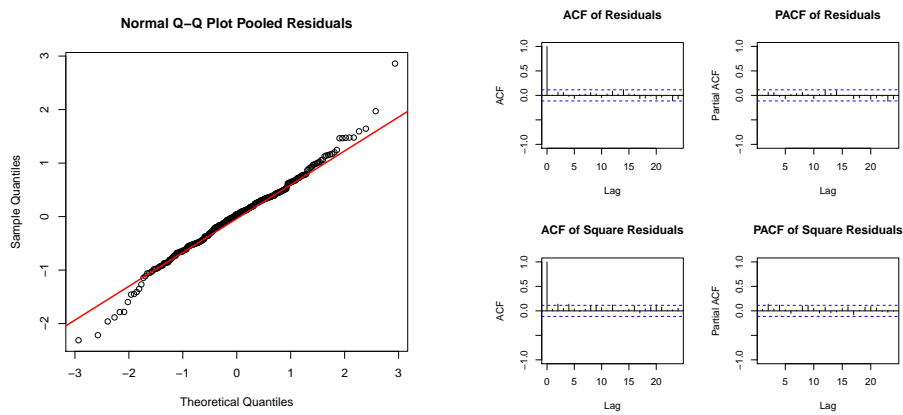


Figure 4: Normal Probability plot and Autocorrelation Function of the residuals from the Complete MSwM model. They are obtained by using the `plotDiag` method

```
> plotProb(mod.mswm, which=2)
```

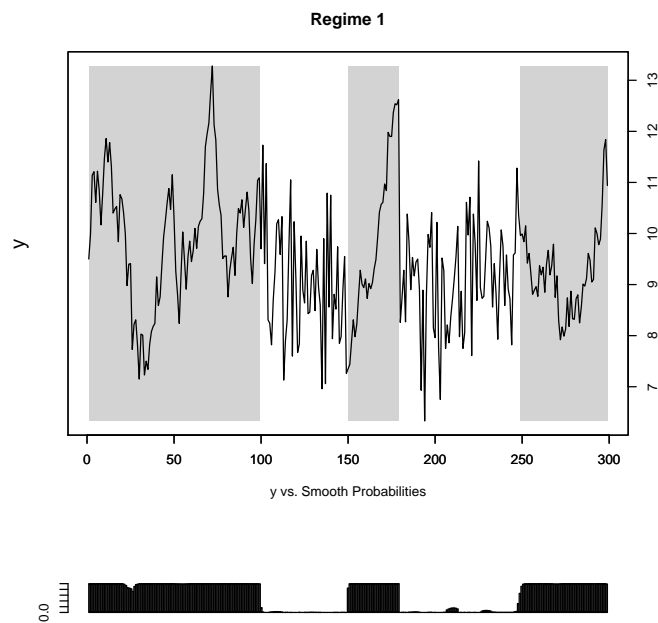


Figure 6: Response variable indicating which observations are associated to regime 1

The graphics show that the periods for each regime have been detected perfectly.

```
> plotReg(mod.mswm, expl="x")
```

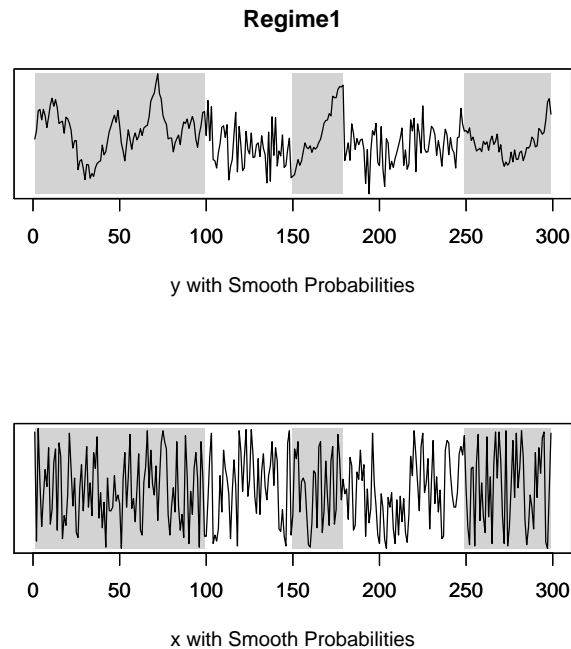


Figure 7: Relationship between x and y locating the two regimes

## 2 Daily Traffic Casualties by car accidents in Spain

The `traffic` data (Fig.8) contains the daily number of deaths in traffic accidents in Spain during the year 2010, the average daily temperature and the daily sum of precipitations. The interest of this data is to study the relation between the number of deaths with the climate conditions. We illustrate the use of a Generalized Markov Switching Model in this case because there exists a different behaviour between the variables during weekends and working days. To avoid a long example, the explanations of how the functions work and repeated results are skipped.

In this example, the response variable is a counting variable. For this reason we fit a Poisson Generalized Linear Model.

```
> model=glm(NDead~Temp+Prec,traffic,family="poisson")  
> summary(model)
```

Call:

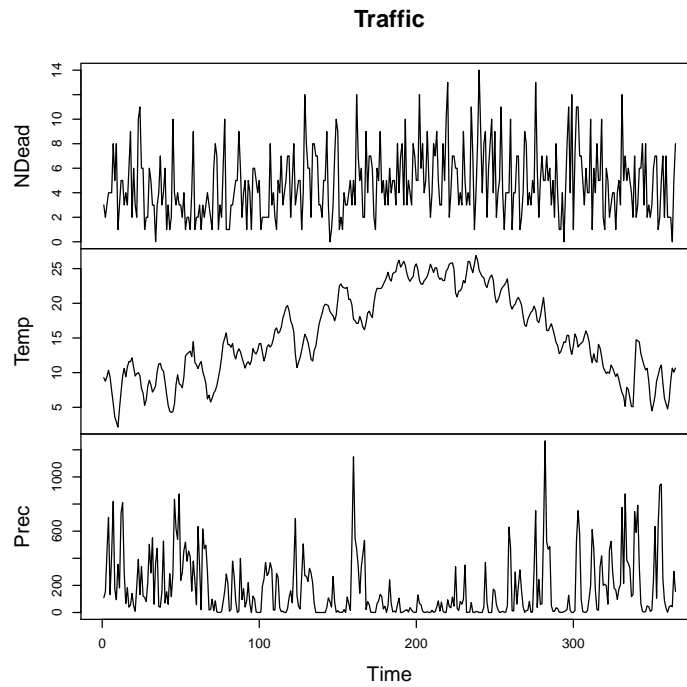


Figure 8: Traffic data: Daily traffic casualties in Spain and climate variables

```
glm(formula = NDead ~ Temp + Prec, family = "poisson", data = traffic)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-3.1571	-1.0676	-0.2119	0.8080	3.0629

Coefficients:

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	1.1638122	0.0808726	14.391	< 2e-16 ***
Temp	0.0225513	0.0041964	5.374	7.7e-08 ***
Prec	0.0002187	0.0001113	1.964	0.0495 *

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

Null deviance: 597.03 on 364 degrees of freedom  
 Residual deviance: 567.94 on 362 degrees of freedom  
 AIC: 1755.9

Number of Fisher Scoring iterations: 5



In the next step, the Markov Switching Model is fitted using `msmFit`. To fit a Generalized Markov Switching Model, the family parameter has to be included. Moreover, the glm's don't have the standard deviation parameter and, because of this, the `sw` parameter doesn't contain its switching parameter.

```
> m1=msmFit(model,k=2,sw=c(T,T,T),family="poisson",control=list(parallel=F))
> summary(m1)
```

#### Markov Switching Model

```
Call: msmFit(object = model, k = 2, sw = c(T, T, T), family = "poisson",
  control = list(parallel = F))
```

```
      AIC      BIC   logLik
1713.878 1772.676 -850.9388
```

#### Coefficients:

##### Regime 1

-----

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)(S)	0.7649	0.1755	4.3584	1.31e-05 ***
Temp(S)	0.0288	0.0082	3.5122	0.0004444 ***
Prec(S)	0.0002	0.0002	1.0000	0.3173105

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

##### Regime 2

-----

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)(S)	1.5659	0.1576	9.9359	< 2e-16 ***
Temp(S)	0.0194	0.0080	2.4250	0.01531 *
Prec(S)	0.0004	0.0002	2.0000	0.04550 *

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

#### Transition probabilities:

	Regime 1	Regime 2
Regime 1	0.7287732	0.4913893
Regime 2	0.2712268	0.5086107

Both states have significant covariates, but the precipitation covariate is only significant in one of the two.

```
> intervals(m1)
```

Aproximate intervals for the coefficients. Level= 0.95

(Intercept):

	Lower	Estimation	Upper
Regime 1	0.4208398	0.7648733	1.108907
Regime 2	1.2569375	1.5658582	1.874779

Temp:

	Lower	Estimation	Upper
Regime 1	0.012728077	0.02884933	0.04497059
Regime 2	0.003708441	0.01939770	0.03508696

Prec:

	Lower	Estimation	Upper
Regime 1	-1.832783e-04	0.0001846684	0.0005526152
Regime 2	-4.808567e-05	0.0004106061	0.0008692979

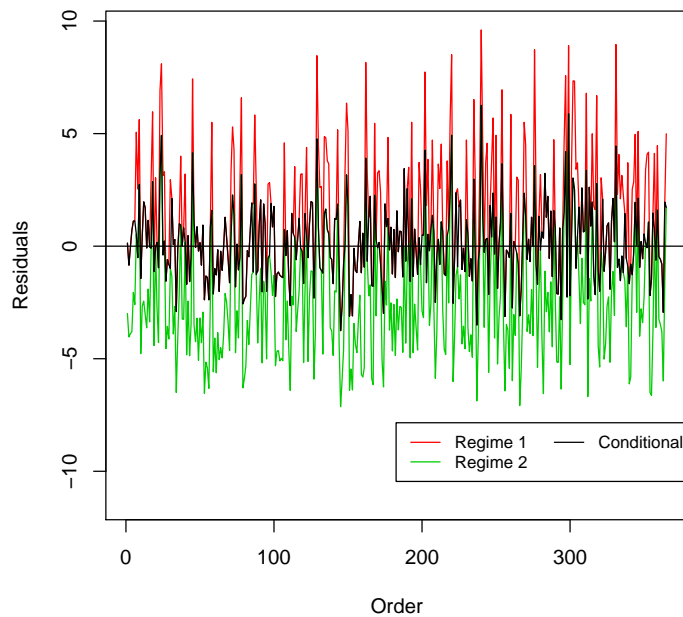


Figure 9: Residuals form the Autoregressive MSM model

The Pearson residuals from Fig. 9 are calculated from an object of class 'MSM.glm' because the model is an extension of a General Linear Model. The residuals have the classical structure of white noise. The residuals aren't au-

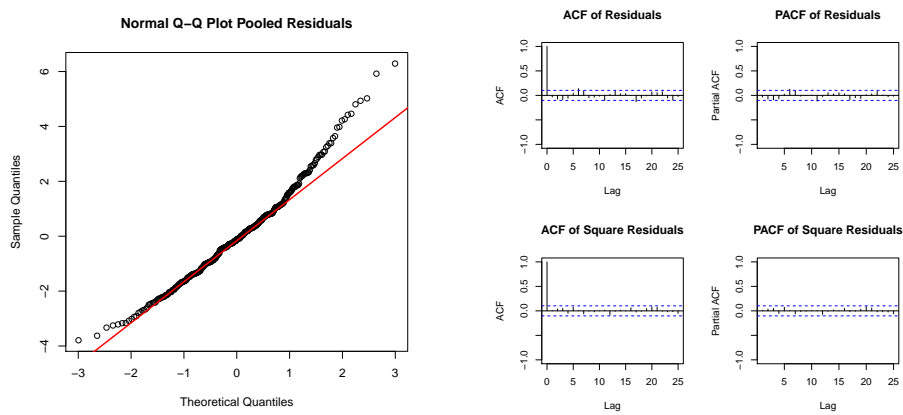


Figure 10: Normal Probability plot and Autocorrelation Function of the residuals from the Autoregressive MSwM model. They are obtained by using the `plotDiag` method

to be correlated but they don't fit very well to a Normal Distribution. However, normality of the Pearson residuals is not a critical condition for generalized linear model validation.

```
> plotProb(m1, which=2)
```

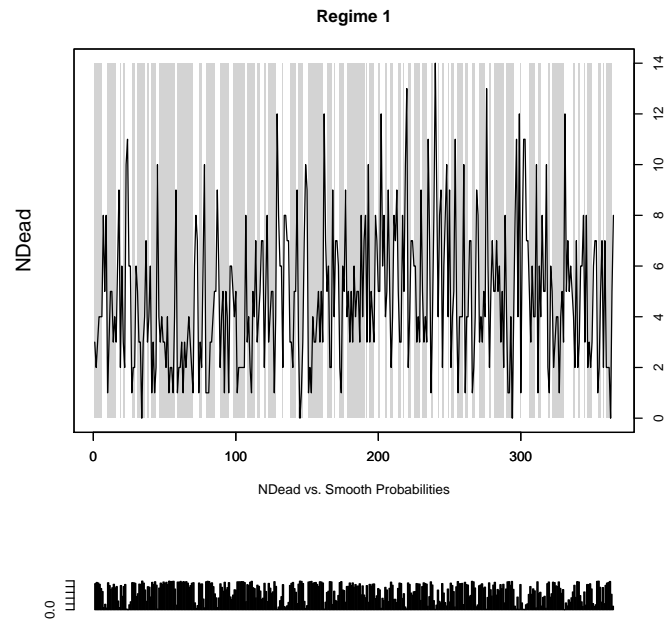


Figure 11: Response variable indicating which observations are associated to regime 1

Using the function `plotProb` we can see how the regimes are distributed in shorts periods because the bigger one contains basically working days.