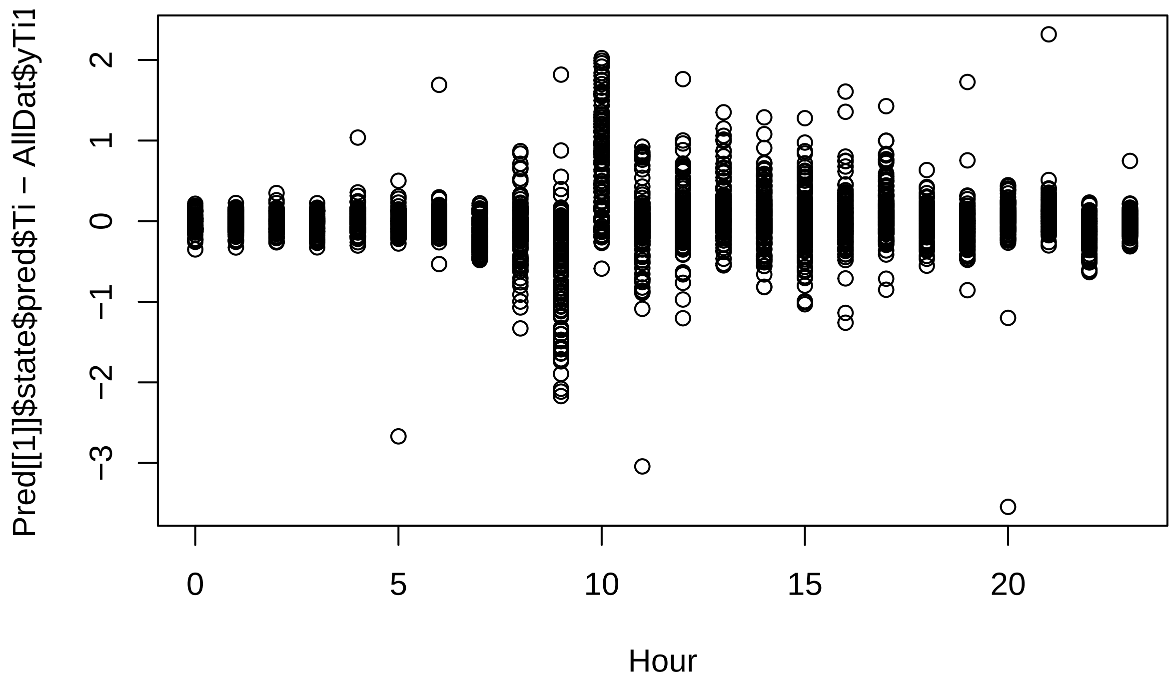
Part 2: Modelling a building using CTSM-R

2a: 2-state model of a single room

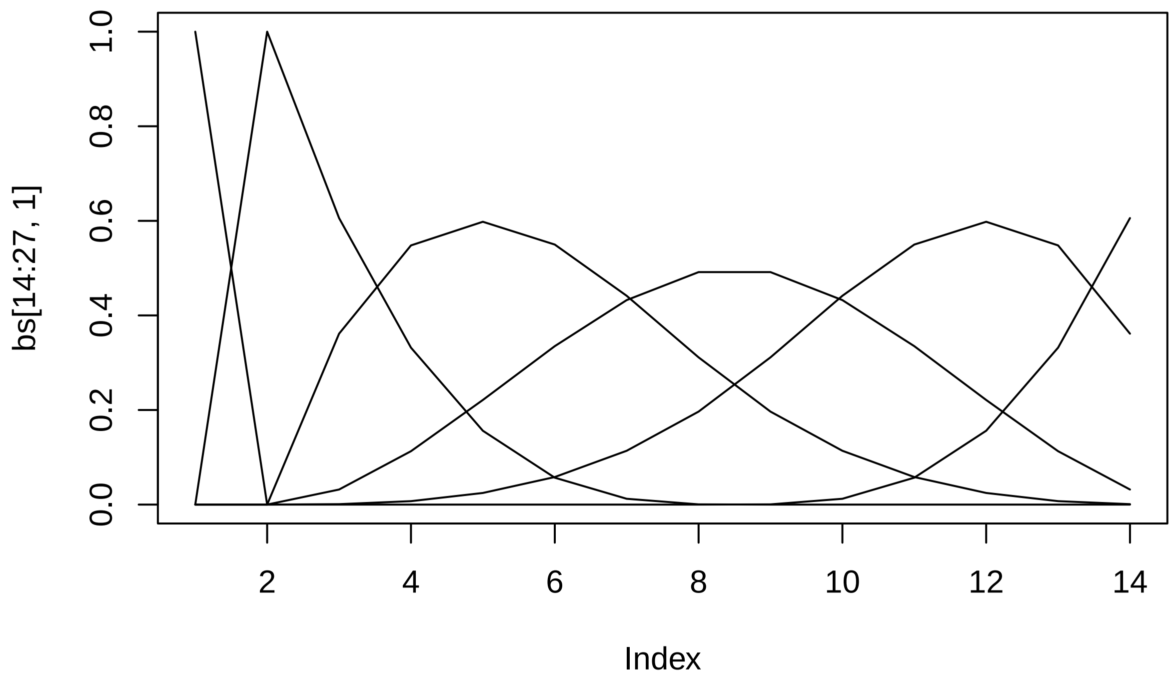
We will estimate the following model where the impact of the measured radiation G_v is scaled relative the sun's angle through the window. Since we do not have access to this information, a non-parametric fit will be done using B-splines.

$$
\begin{aligned}
dT_i &= \frac{1}{C_i}\left(\frac{1}{R_{ia}}\left(T_a - T_i\right) + \frac{1}{R_{im}}\left(T_m - T_i\right) + \Phi + \left(\sum_{k=1}^{N} a_k bs_k(t)\right) G_v\right) dt + \sigma_1 dw_1 \\
dT_m &= \frac{1}{C_m}\left(\frac{1}{R_{im}}\left(T_i - T_m\right)\right) dt + \sigma_2 dw_2. \\
yT_i &= T_i + e_1,
\end{aligned}
$$

```r
#install.packages("ctsmr", repo = "http://ctsm.info/repo/dev")
#install.packages("pkgbuild")

# For git pushing
## git push https://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@github.com/davidripsen/3-Assignment.git

library(ctsmr)
library(splines)
source("CompEx3_E18/sdeTiTm.R")
# Load data
if (Sys.info()[7] == "davidipsen")
  {path <- "~/Documents/DTU/3. Semester (MSc)/Advanced Time Series/Assignments/3-Assignment/CompEx3_E18
} else {path <- "CompEx3_E18/"}
load(paste0(path,"Exercise3.RData"))
#AllDat

########## Initial model ############
  fit1 <- sdeTiTm(AllDat,AllDat$yTi1,AllDat$Ph1) # Original model

  summary(fit1,extended=TRUE)
  fit1$loglik

  Hour <- as.numeric(strftime(AllDat$date, format="%H"))

  Pred <- predict(fit1)
  plot(Pred[[1]]$state$pred$Ti - AllDat$yTi1 ~ Hour)
```




```
# Fit only splines for radiation hours
#plot(AllDat$Gv ~ Hour) #


idx <- (Hour>8 & Hour < 23) # It is impossible to fit a window area for the hours without any sun, so
bs = bs(Hour[idx],df=5,intercept=TRUE) # Dvs. 4 knots / 5 basis splines

# What does the splines look like?
plot(bs[14:27,1],type='l')
lines(bs[ 14:27,2])
lines(bs[ 14:27,3])
lines(bs[ 14:27,4])
lines(bs[ 14:27,5])
```




```
  bs1 <- bs2 <- bs3 <- bs4 <- bs5 <- bs6 <- numeric(dim(AllDat)[1])

  bs1[idx] = bs[,1]
  bs2[idx] = bs[,2]
  bs3[idx] = bs[,3]
  bs4[idx] = bs[,4]
  bs5[idx] = bs[,5]

  AllDat$bs1 = bs1
  AllDat$bs2 = bs2
  AllDat$bs3 = bs3
  AllDat$bs4 = bs4
  AllDat$bs5 = bs5


### IMPLEMENT THE MENTIONED MODEL ###
source(paste0(path,"sdeTiTmAv.R"))
fit2 <- sdeTiTmAv(AllDat,AllDat$yTi1,AllDat$Ph1)
```

Let's compare the two models

```
sprintf('Model 1: logL = %f', fit1$loglik)
```

```
## [1] "Model 1: logL = -1099.990110"
```

```
sprintf('Model 2: logL = %f', fit2$loglik)
```

```
## [1] "Model 2: logL = -17.228633"
```

I.e. we see a very large improvement in likelihood (for only 4 extra parameters).

```
summary(fit2, extended=T)
```

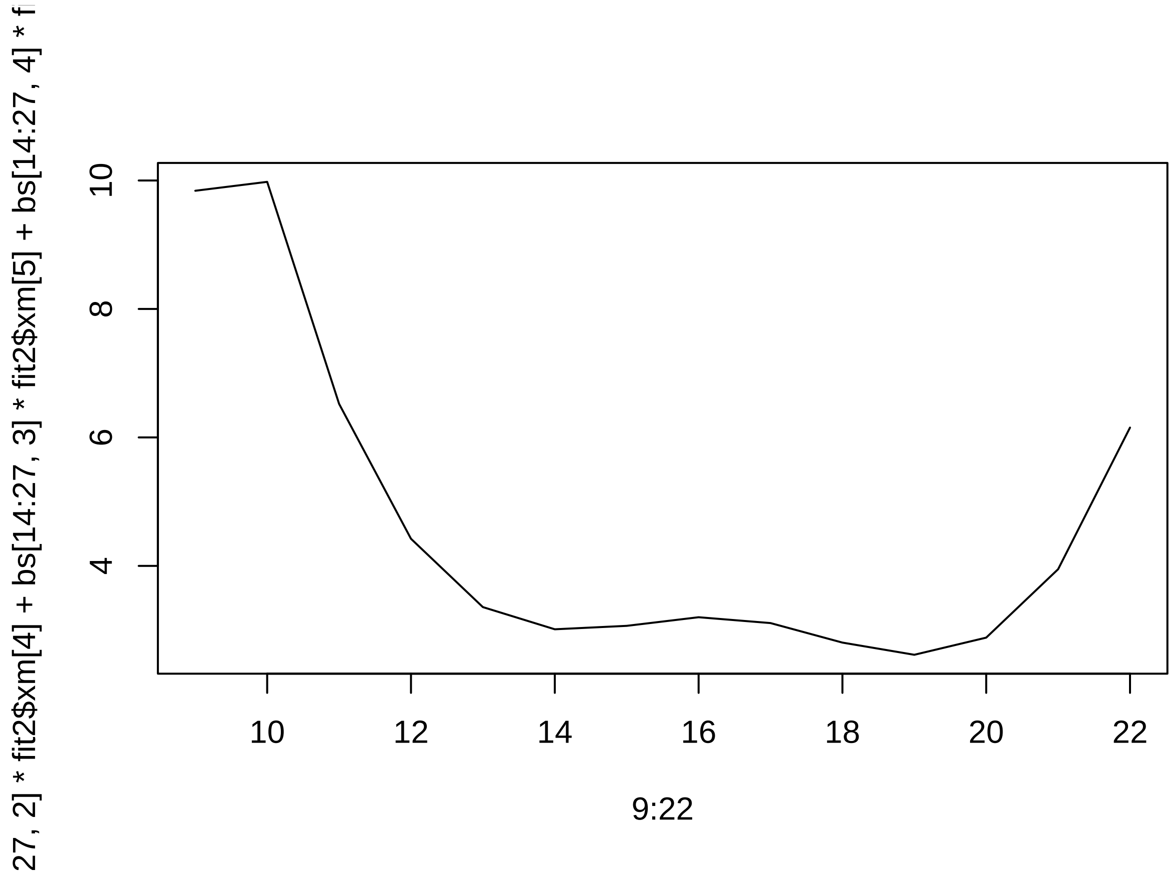
```
## Coefficients:
##         Estimate  Std. Error     t value    Pr(>|t|)      dF/dPar dPen/dPar
```

```
## Ti0  2.3600e+01  1.4918e-01  1.5819e+02  0.0000e+00  5.4554e-04    0.0004
## Tm0  2.1274e+01  7.7689e-01  2.7384e+01  0.0000e+00 -3.3116e-04    0.0002
## a1   9.9785e+00  6.0430e-02  1.6513e+02  0.0000e+00 -3.3543e-03   21.6319
## a2   7.9155e-01  8.3401e-01  9.4910e-01  3.4265e-01 -1.3728e-05    0.0000
## a3   6.0005e+00  1.1136e+00  5.3885e+00  7.6532e-08 -7.9965e-05    0.0004
## a4   4.3394e-04  1.9158e-03  2.2650e-01  8.2083e-01  6.7033e-05    0.0000
## a5   9.8398e+00  7.8348e-01  1.2559e+01  0.0000e+00  3.6179e-03    0.3835
## Ci   8.4165e+00  1.9981e-01  4.2123e+01  0.0000e+00 -8.1438e-05    0.0000
## Cm   8.6987e+04  1.1818e+05  7.3604e-01  4.6176e-01  1.5940e-04    0.0051
## e11 -2.0223e+01  1.5829e+01 -1.2776e+00  2.0150e-01 -3.7567e-04    0.0001
## p11 -1.6318e+00  2.2926e-02 -7.1177e+01  0.0000e+00 -1.1393e-04    0.0000
## p22 -8.6558e-01  4.9709e-02 -1.7413e+01  0.0000e+00 -1.9574e-05    0.0000
## Ria  1.0880e+01  3.4931e+00  3.1147e+00  1.8582e-03  2.5151e-05    0.0000
## Rim  4.6964e-01  1.7945e-02  2.6170e+01  0.0000e+00 -8.9689e-05    0.0000
##
## Correlation of coefficients:
##     Ti0   Tm0   a1    a2    a3    a4    a5    Ci    Cm    e11   p11   p22
## Tm0  0.25
## a1   0.02 -0.04
## a2   0.02 -0.09 -0.04
## a3  -0.03  0.01  0.13 -0.43
## a4  -0.12 -0.41 -0.60  0.07 -0.06
## a5   0.12  0.41  0.67 -0.04  0.07 -0.99
## Ci  -0.01  0.10  0.01  0.08 -0.03 -0.05  0.06
## Cm  -0.02  0.13  0.24 -0.08  0.07  0.44 -0.35  0.01
## e11  0.02 -0.13 -0.27  0.08 -0.08 -0.41  0.32 -0.01 -1.00
## p11  0.00 -0.11  0.05  0.15 -0.11  0.02 -0.02 -0.12 -0.01  0.01
## p22 -0.07  0.04  0.01 -0.27 -0.01 -0.04  0.04  0.24  0.03 -0.03 -0.44
## Ria  0.10 -0.28  0.04  0.27  0.35  0.08 -0.06  0.06 -0.05  0.03  0.08 -0.22
## Rim  0.00 -0.20 -0.02 -0.11 -0.25  0.10 -0.11 -0.20 -0.01  0.01  0.37  0.02
##     Ria
## Tm0
## a1
## a2
## a3
## a4
## a5
## Ci
## Cm
## e11
## p11
## p22
## Ria
## Rim  0.00
```

```
#plot(9:22, bs[14:27,1]*fit2$xm[3]+bs[14:27,2]*fit2$xm[4]+bs[14:27,3]*fit2$xm[5]+bs[14:27,4]*fit2$xm[6]
```

We see that a4 and a5 have extremely large p-values and a correlation of **1** so it would make sense to reduce the model. First, let's examine the spline-fit

```
plot(9:22, bs[14:27,1]*fit2$xm[3]+bs[14:27,2]*fit2$xm[4]+bs[14:27,3]*fit2$xm[5]+bs[14:27,4]*fit2$xm[6]+
```



Remember, that the above fit is not the actual input radiation to the room, but it is a weighting of the actual radiation.

2b

```
# Load data
if (Sys.info()[7] == "davidipsen")
  {path <- "~/Documents/DTU/3. Semester (MSc)/Advanced Time Series/Assignments/3-Assignment/CompEx3_E18
} else {path <- "CompEx3_E18/"}
load(paste0(path,"Exercise3.RData"))
D = AllDat
head(D)
```

```
##                  date    t yTi1 yTi2 yTi3 yTi4   Ta    Gv       Ph1        Ph2
## 1 2014-12-22 09:00:00 1233 23.6 22.3 22.7 22.1  4.9 0.084 10.700257 12.65397467
## 2 2014-12-22 10:00:00 1234 24.4 22.6 23.1 22.4  8.4 0.202 10.460387 10.38274844
## 3 2014-12-22 11:00:00 1235 24.4 22.8 23.5 22.7 10.8 0.315 10.046700  6.56453906
## 4 2014-12-22 12:00:00 1236 24.6 23.0 23.7 23.0 12.9 0.375  9.560008  2.42302757
## 5 2014-12-22 13:00:00 1237 25.1 23.2 23.6 23.2 15.1 0.390  8.922674  0.00000000
## 6 2014-12-22 14:00:00 1238 25.2 23.2 23.7 23.3 15.9 0.351  8.628342  0.03939882
```

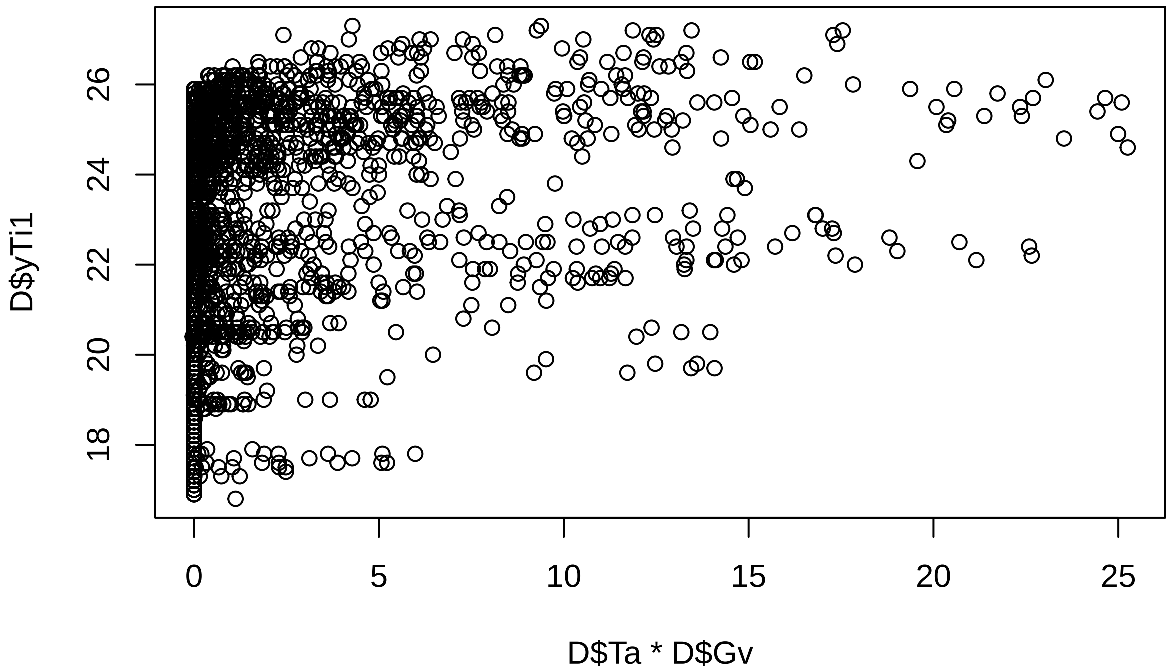
```
tail(D)
```

```
##                     date    t yTi1 yTi2 yTi3 yTi4   Ta    Gv Ph1 Ph2
## 3106 2015-04-30 18:00:00 4338 26.6 26.0 25.9 25.3 23.6 0.319   0   0
## 3107 2015-04-30 19:00:00 4339 26.4 25.9 25.9 25.1 23.2 0.171   0   0
## 3108 2015-04-30 20:00:00 4340 26.2 25.8 25.8 25.0 20.2 0.038   0   0
```

```
## 3109 2015-04-30 21:00:00 4341 25.9 25.6 25.6 25.0 21.0 0.001   0   0
## 3110 2015-04-30 22:00:00 4342 25.8 25.6 25.5 24.9 22.4 0.000   0   0
## 3111 2015-04-30 23:00:00 4343 25.7 25.5 25.4 24.9 22.1 0.000   0   0
```

Visualisations

```
plot(D$Ta * D$Gv, D$yTi1)
```



Let's try expanding the model. 1. Note how the effect of the temperature in room 3 and 4 affects only room 1 through the medium of room 2. In other words: Y_1 is *conditionally independent* of Y_3 and Y_4 when Y_2 is known. —- disadvantage: Time delay for a change in T2 before it enters T1 -> enter Tm before -> Make Tm also a function of T2? == Men hey, er det ikke bare via Thermal Mass (Tm) at room1 bliver påvirket? 2. Dvs. dTm = … Org. … + 1/R_21*(T2-T1x)