Week 6 exercise solutions

Ali Movasati, Isabelle Cretton, Tristan Koning

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```
# Set global code chunk options
knitr::opts_chunk$set(warning = FALSE)

# load required libraries
library(skimr)
library(ggplot2)
library(np)

## Nonparametric Kernel Methods for Mixed Datatypes (version 0.60-17)
## [vignette("np_faq",package="np") provides answers to frequently asked questions]
## [vignette("np",package="np") an overview]
## [vignette("entropy_np",package="np") an overview of entropy-based methods]

library(splines)
library(sm)
## Package 'sm', version 2.2-6.0: type help(sm) for summary information
```

Exercise 1

(a)

```
# Load and explore data
medflies <- read.table(file = "data/medflies.txt", sep = "\t", header = TRUE)
medflies$mort.rate <- as.numeric(medflies$mort.rate)
skim(medflies)</pre>
```

Table 1: Data summary

Name	medflies
Number of rows	173
Number of columns	3
Column type frequency:	
numeric	3

iab.	les
	iabl

None

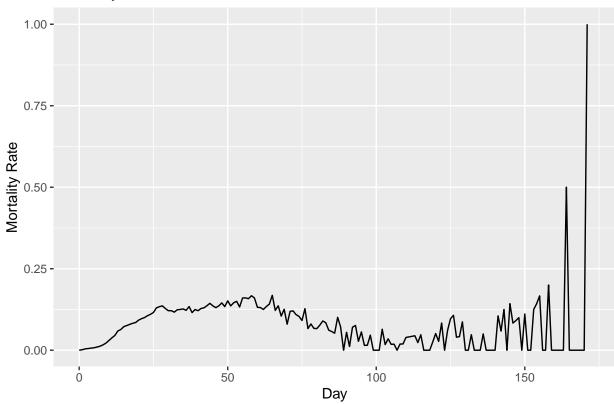
Variable type: numeric

skim_variablen_	_missing com	plete_rat	se mean	sd	p0	p25	p50	p75	p100	hist
day	0	1.00	86.00	50.08	0	43.00	86.00	129.00	172	
living	0	1.00	148501.07	339536.10	0	23.00	115.00	30360.00	1203646	
mort.rate	1	0.99	0.08	0.10	0	0.01	0.07	0.12	1	

str(medflies)

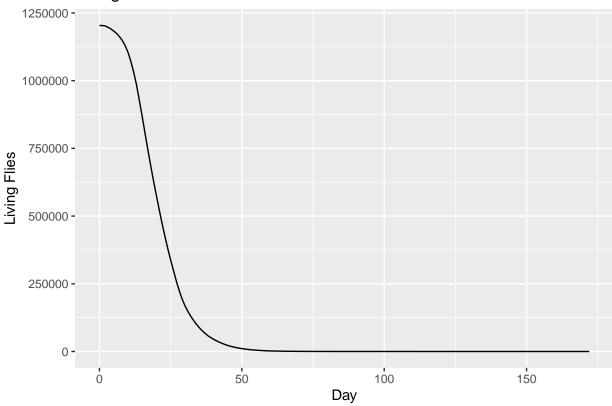
```
## 'data.frame': 173 obs. of 3 variables:
## $ day : int 0 1 2 3 4 5 6 7 8 9 ...
## $ living : int 1203646 1203646 1201913 1197098 1191020 1183419 1174502 1163026 1148693 1129836 .
## $ mort.rate: num 0 0.0014 0.004 0.0051 0.0064 0.0075 0.0098 0.0123 0.0164 0.0218 ...
## Graphical EDA
ggplot(medflies, aes(x = day, y = mort.rate)) +
    geom_line() +
    labs(title = "Mortality Rate Over Time", x = "Day", y = "Mortality Rate")
```

Mortality Rate Over Time



```
ggplot(medflies, aes(x = day, y = living)) +
geom_line() +
labs(title = "Living Flies Over Time", x = "Day", y = "Living Flies")
```

Living Flies Over Time

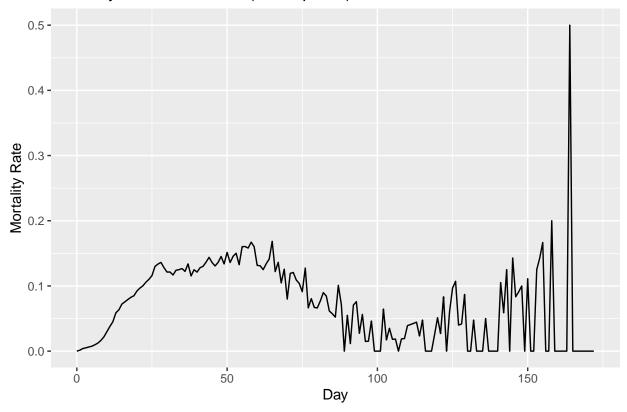


(b)

```
for (i in 1:(nrow(medflies) - 2)) {
  medflies$mort.rate2[i] <- (medflies$living[i] - medflies$living[i + 1]) / medflies$living[i]
}

ggplot(medflies, aes(x = day, y = mort.rate2)) +
  geom_line() +
  labs(title = "Mortality Rate Over Time (recomputed)", x = "Day", y = "Mortality Rate")</pre>
```

Mortality Rate Over Time (recomputed)



mort.rate and mort.rate2 are very similar, but not identical. mort.rate2 is slightly higher than mort.rate. This is likely due to the fact that the original mort.rate was rounding to 4 decimal places, while mort.rate2 is rounding on a higher precision.

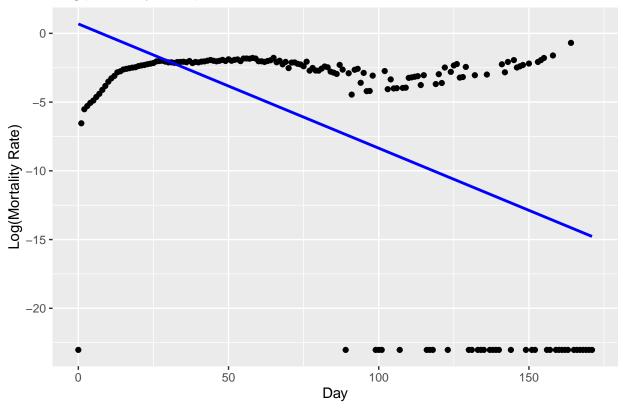
(c)

```
# Remove NA values
medflies <- medflies[complete.cases(medflies), ]</pre>
medflies$mort.rate2[medflies$mort.rate2 == 0] <- 1e-10</pre>
# Transform the mortality rate
medflies$log_mort_rate2 <- log(medflies$mort.rate2)</pre>
# Fit a linear regression model
model_A <- lm(log_mort_rate2 ~ day, data = medflies)</pre>
summary(model_A)
##
## Call:
## lm(formula = log_mort_rate2 ~ day, data = medflies)
##
## Residuals:
##
                                  ЗQ
       Min
                 1Q Median
                                          Max
```

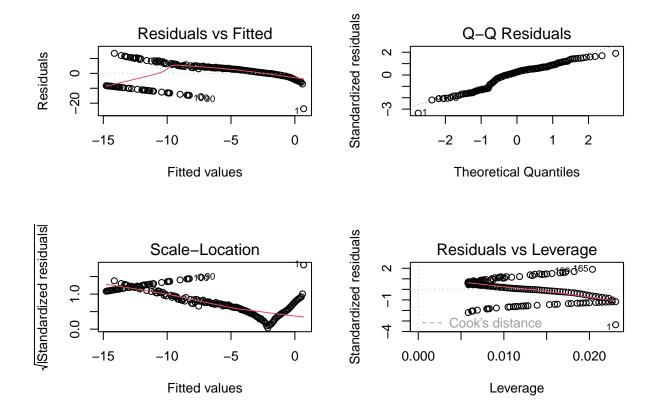
```
## -23.712 -4.530
                   1.830 4.581 13.446
##
## Coefficients:
              Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) 0.68625
                          1.08520
                                    0.632
              -0.09040
                          0.01098 -8.236 4.54e-14 ***
## day
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 7.147 on 170 degrees of freedom
## Multiple R-squared: 0.2852, Adjusted R-squared: 0.281
## F-statistic: 67.84 on 1 and 170 DF, p-value: 4.54e-14
ggplot(medflies, aes(x = day, y = log_mort_rate2)) +
 geom_point() +
 geom_smooth(method = "lm", se = FALSE, color = "blue") +
 labs(title = "Log(Mortality Rate) Over Time", x = "Day", y = "Log(Mortality Rate)")
```

$geom_smooth()$ using formula = 'y ~ x'

Log(Mortality Rate) Over Time



```
par(mfrow = c(2, 2))
plot(model_A)
```

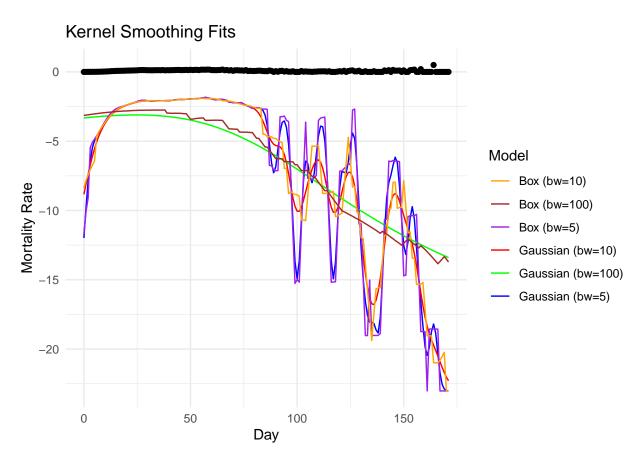


Looking at the plot of the model, we can observe a decrease in the mortality rate over time. However, we can spot that the first few days indeed to have a linear increase in the log(Mortality Rate), therefore there does exist some exponential growth in the beginning. This stops after roughly 10-15 days.

(d)

```
# Fit models with different kernels and bandwidths
gaussian_A <- ksmooth(medflies$day, medflies$log_mort_rate2, kernel = "normal", bandwidth = 5)</pre>
gaussian_B <- ksmooth(medflies$day, medflies$log_mort_rate2, kernel = "normal", bandwidth = 10)</pre>
gaussian_C <- ksmooth(medflies$day, medflies$log_mort_rate2, kernel = "normal", bandwidth = 100)</pre>
box_A <- ksmooth(medflies$day, medflies$log_mort_rate2, kernel = "box", bandwidth = 5)
box_B <- ksmooth(medflies$day, medflies$log_mort_rate2, kernel = "box", bandwidth = 10)
box_C <- ksmooth(medflies$day, medflies$log_mort_rate2, kernel = "box", bandwidth = 100)
fitted values <- data.frame(
  day = medflies$day,
  mort.rate2 = medflies$mort.rate2,
  gaussian_A = gaussian_A$y,
  gaussian_B = gaussian_B$y,
  gaussian_C = gaussian_C$y,
  box_A = box_A$y,
  box_B = box_B y,
  box_C = box_C$y
```

```
ggplot(medflies, aes(x = day, y = mort.rate2)) +
   geom_point() +
   geom_line(data = fitted_values, aes(x = day, y = gaussian_A, color = "Gaussian (bw=5)")) +
   geom_line(data = fitted_values, aes(x = day, y = gaussian_B, color = "Gaussian (bw=10)")) +
   geom_line(data = fitted_values, aes(x = day, y = gaussian_C, color = "Gaussian (bw=100)")) +
   geom_line(data = fitted_values, aes(x = day, y = box_A, color = "Box (bw=5)")) +
   geom_line(data = fitted_values, aes(x = day, y = box_B, color = "Box (bw=10)")) +
   geom_line(data = fitted_values, aes(x = day, y = box_C, color = "Box (bw=100)")) +
   scale_color_manual(name = "Model", values = c("Gaussian (bw=5)" = "blue", "Gaussian (bw=10)" = "red",
   labs(title = "Kernel Smoothing Fits", x = "Day", y = "Mortality Rate") +
   theme_minimal()
```

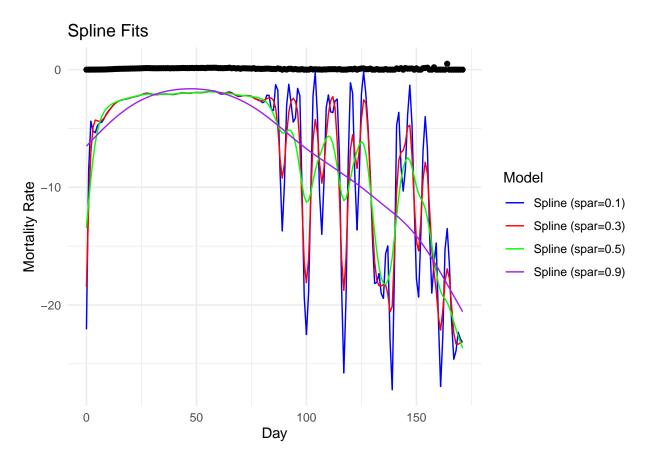


(e) i

```
spline_A <- smooth.spline(medflies$day, medflies$log_mort_rate2, spar = 0.1)
spline_B <- smooth.spline(medflies$day, medflies$log_mort_rate2, spar = 0.3)
spline_C <- smooth.spline(medflies$day, medflies$log_mort_rate2, spar = 0.5)
spline_D <- smooth.spline(medflies$day, medflies$log_mort_rate2, spar = 0.9)
fitted_values <- data.frame(
    day = medflies$day,</pre>
```

```
mort.rate2 = medflies$mort.rate2,
    spline_A = predict(spline_A)$y,
    spline_B = predict(spline_B)$y,
    spline_C = predict(spline_C)$y,
    spline_D = predict(spline_D)$y
)

ggplot(medflies, aes(x = day, y = mort.rate2)) +
    geom_point() +
    geom_line(data = fitted_values, aes(x = day, y = spline_A, color = "Spline (spar=0.1)")) +
    geom_line(data = fitted_values, aes(x = day, y = spline_B, color = "Spline (spar=0.3)")) +
    geom_line(data = fitted_values, aes(x = day, y = spline_C, color = "Spline (spar=0.5)")) +
    geom_line(data = fitted_values, aes(x = day, y = spline_D, color = "Spline (spar=0.5)")) +
    geom_line(data = fitted_values, aes(x = day, y = spline_D, color = "Spline (spar=0.9)")) +
    scale_color_manual(name = "Model", values = c("Spline (spar=0.1)" = "blue", "Spline (spar=0.3)" = "relabs(title = "Spline Fits", x = "Day", y = "Mortality Rate") +
    theme_minimal()
```



(e) ii

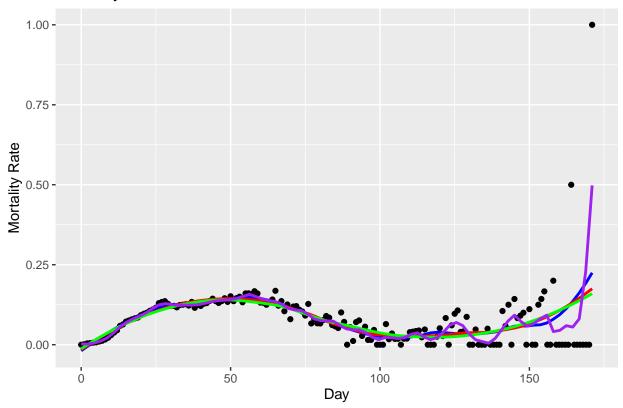
```
# Fit a model with different spans
model_B <- loess(mort.rate ~ day, data = medflies, span = 0.3)
model_C <- loess(mort.rate ~ day, data = medflies, span = 0.5)
model_D <- loess(mort.rate ~ day, data = medflies, span = 0.7)</pre>
```

```
model_E <- loess(mort.rate ~ day, data = medflies, span = 0.1)

# Plot the models
ggplot(medflies, aes(x = day, y = mort.rate)) +
    geom_point() +
    geom_smooth(method = "loess", se = FALSE, color = "blue", span = 0.3) +
    geom_smooth(method = "loess", se = FALSE, color = "red", span = 0.5) +
    geom_smooth(method = "loess", se = FALSE, color = "green", span = 0.7) +
    geom_smooth(method = "loess", se = FALSE, color = "purple", span = 0.1) +
    labs(title = "Mortality Rate Over Time", x = "Day", y = "Mortality Rate")</pre>
```

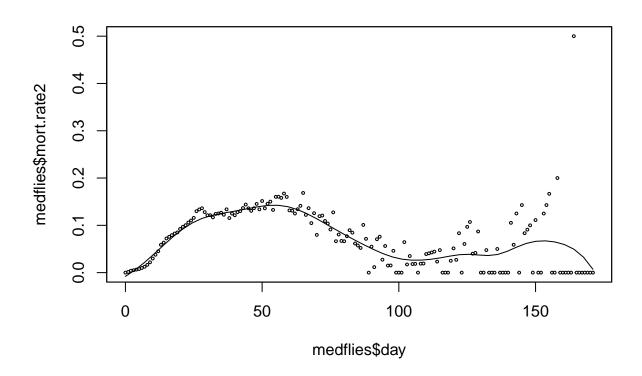
```
## `geom_smooth()` using formula = 'y ~ x'
```

Mortality Rate Over Time



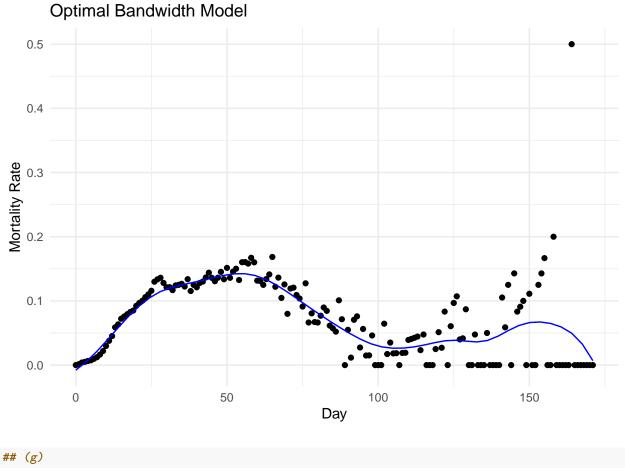
(f)

```
opt_bw <- hcv(medflies$day, medflies$mort.rate2, kernel = "normal")
model_opt <- sm.regression(x = medflies$day, y = medflies$mort.rate2, h = opt_bw)</pre>
```



```
fitted_values_opt <- data.frame(
   day = model_opt$eval.points,
   mort.rate2 = model_opt$estimate
)

# Plot the data and the resulting fit
ggplot(medflies, aes(x = day, y = mort.rate2)) +
   geom_point() +
   geom_line(data = fitted_values_opt, aes(x = day, y = mort.rate2), color = "blue") +
   labs(title = "Optimal Bandwidth Model", x = "Day", y = "Mortality Rate") +
   theme_minimal()</pre>
```



TODO

(h)

We want to use non-parametric models when we dont know the distribution of our data, have very little data to work with or if the data does not follow a known distribution that allows it to be used in a parametric model.

A question that could be asked is whether the chance of getting cancer given different lifestyle choices? This could be solved more easily with non-parametric rather than parametric model since the interactions of a persons lifestyle will probably not follow a certain distribution.

A question that can be answered with a linear model, could be if smoking affects the cholesterol level.