hw 6

The Child Mortality dataset (under LS Content, or the 'child' data frame in the "eha" package for R) contains data on child mortality in Sweden during the 1800's.

```
library(eha)
## Warning: package 'eha' was built under R version 4.1.3
library(survival)
child = eha::child
head(child)
##
        id
             m.id
                     sex socBranch birthdate enter
                                                        exit event illeg m.age
## 3
         9 246606
                           farming 1853-05-23
                                                   0 15.000
                                                                 0
                                                                      no 35.009
                    male
                                                                      no 30.609
       150 377744
                    male
                           farming 1853-07-19
                                                   0 15.000
## 47
       158 118277
                                                   0 15.000
                                                                      no 29.320
                    male
                             worker 1861-11-17
                                                                 0
## 54
      178 715337
                    male
                           farming 1872-11-16
                                                   0 15.000
                                                                 0
                                                                      no 41.183
## 78 263 978617 female
                             worker 1855-07-19
                                                   0
                                                     0.559
                                                                      no 42.138
                                                                 1
## 102 342 282943
                    male
                           farming 1855-09-29
                                                   0
                                                      0.315
                                                                      no 32.931
```

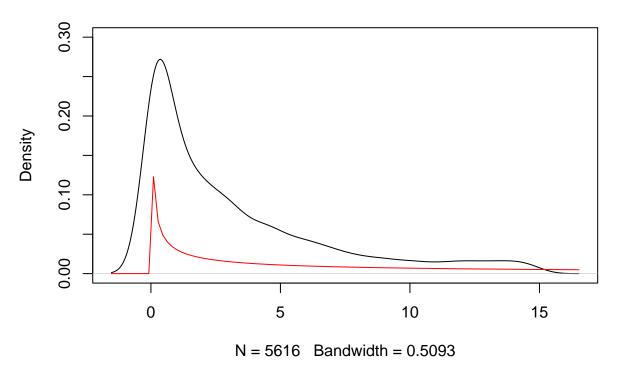
1. Evaluate the data in the dataset to see how well it follows a Weibull distribution. Give a 1-2 sentence explanation and description of plots or other diagnostics used.

From the plots below we see that the child data looks like it follows a scaled weibull distribution. We used the optim function to find the MLE for the parameters of the distribution.

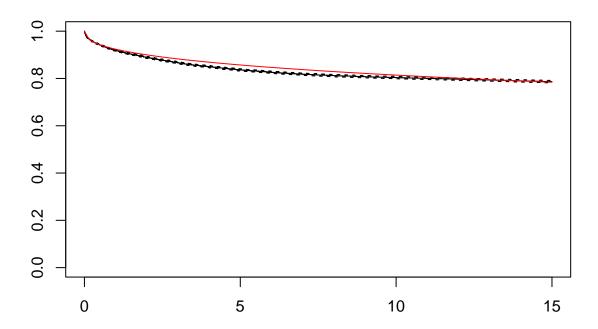
```
## [1] -4.272407
```

```
o2 <- optim(c(4,2), fn=logLikWeib2,
           control=list(fnscale= -1),
           tt = child$exit,
           status = child$event
)
o2$par
## [1] 6.120841 2.413445
survreg(Surv(exit, event) ~ 1,
 data=child,
dist='weibull')
## Call:
## survreg(formula = Surv(exit, event) ~ 1, data = child, dist = "weibull")
## Coefficients:
## (Intercept)
##
      6.120483
## Scale= 2.413115
## Loglik(model) = -25165 Loglik(intercept only) = -25165
## n= 26574
plot(density(child$exit[child$event==1]),
     type='1', ylim=c(0,0.3))
curve(dweibull(x, 1/o2$par[2], exp(o2$par[1])),
 add=TRUE, col='red')
```

density.default(x = child\$exit[child\$event == 1])



Data and Weibull



2. Fit a parametric regression model with the Weibull distribution to the data (use exit and event variables, do not worry about enter) with sex of the child, mothers age, and the social group (socBranch) as predictors.

```
colnames(child)
##
    [1] "id"
                     "m.id"
                                 "sex"
                                             "socBranch" "birthdate" "enter"
   [7] "exit"
                    "event"
                                 "illeg"
                                             "m.age"
fit1 = survreg(Surv(exit, event) ~ sex + socBranch + m.age,
             data=child, dist = "weibull")
summary(fit1)
##
## Call:
## survreg(formula = Surv(exit, event) ~ sex + socBranch + m.age,
##
       data = child, dist = "weibull")
##
                        Value Std. Error
## (Intercept)
                      6.65062
                                  0.28152 23.62 < 2e-16
## sexfemale
                      0.19949
                                  0.06454 3.09 0.00199
## socBranchfarming
                      0.03944
                                  0.22267 0.18 0.85941
## socBranchbusiness -0.82289
                                  0.34028 -2.42 0.01560
## socBranchworker
                     -0.24225
                                  0.22749 -1.06 0.28693
```

3. Further explore the fit in part 2 to see if a non-linear effect of age gives a better fit and if any interactions are important.

A non-linear effect for age lowers the AIC and so we believe it improves the fit of the model. Adding in an interaction between sex and social branch does not improve the model fit so we leave it out.

```
##
## Call:
## survreg(formula = Surv(exit, event) ~ sex + socBranch + pspline(m.age,
##
       df = 4), data = child, dist = "weibull")
##
                       Value Std. Error
## (Intercept)
                                 0.7397 7.16 8.3e-13
                      5.2926
## sexfemale
                      0.1998
                                 0.0645 3.10
                                                0.002
## socBranchfarming
                      0.0420
                                 0.2226 0.19
                                                0.850
## socBranchbusiness -0.8244
                                 0.3401 - 2.42
                                                0.015
## socBranchworker
                    -0.2387
                                 0.2274 - 1.05
                                                0.294
## ps(m.age)3
                      0.3702
                                 0.3878 0.95
                                                0.340
## ps(m.age)4
                                 0.6309 1.17
                                                0.243
                      0.7362
## ps(m.age)5
                      0.9535
                                 0.7228 1.32
                                                0.187
## ps(m.age)6
                                 0.7204 1.19
                      0.8567
                                                0.234
## ps(m.age)7
                      0.8512
                                 0.7081 1.20
                                                0.229
## ps(m.age)8
                                 0.7070 1.21
                      0.8543
                                                0.227
## ps(m.age)9
                      0.7396
                                 0.7085 1.04
                                                0.297
## ps(m.age)10
                      0.5332
                                 0.7100 0.75
                                                0.453
## ps(m.age)11
                      0.4436
                                 0.7138 0.62
                                                0.534
## ps(m.age)12
                                 0.7432 0.56
                      0.4128
                                                0.579
## ps(m.age)13
                      0.3992
                                 0.8589 0.46
                                                0.642
## ps(m.age)14
                      0.3889
                                 1.0964 0.35
                                                0.723
## Log(scale)
                      0.8797
                                 0.0129 68.34 < 2e-16
##
## Scale= 2.41
##
## Weibull distribution
## Loglik(model) = -25137.2
                             Loglik(intercept only)= -25165
## Chisq= 55.6 on 7.5 degrees of freedom, p= 1.9e-09
## Number of Newton-Raphson Iterations: 6 16
## n= 26574
```

```
AIC(fit1)
## [1] 50298.35
AIC(fit2)
## [1] 50293.32
  4. Refit your model from part 3 using a distribution other than the Weibull. Briefly describe how this fit
     compares to the previous one.
We refit the model using a Gaussian distribution instead of the Weibull. This significantly increased AIC.
However, fitting the data to a lognormal decreased AIC giving us the best fit of all the models yet. This
holds true for BIC as well.
fit3 = survreg(Surv(exit, event) ~ sex + socBranch + pspline(m.age, df = 4),
              data=child, dist = "gaussian")
fit4 = survreg(Surv(exit, event) ~ sex + socBranch + pspline(m.age, df = 4),
              data=child, dist = "lognormal")
AIC(fit1)
## [1] 50298.35
AIC(fit2)
## [1] 50293.32
AIC(fit3)
## [1] 64629.14
AIC(fit4)
## [1] 49911.91
# BIC
BIC(fit1)
## [1] 50355.67
BIC(fit2)
```

[1] 50370.85

BIC(fit3)

[1] 64706.05

BIC(fit4)

[1] 49989.37