Assignment10; STAT 689

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3/21/2018

Question 10

10A

```
library("mgcv")
library("HRW")
data(ragweed)
str(ragweed)
```

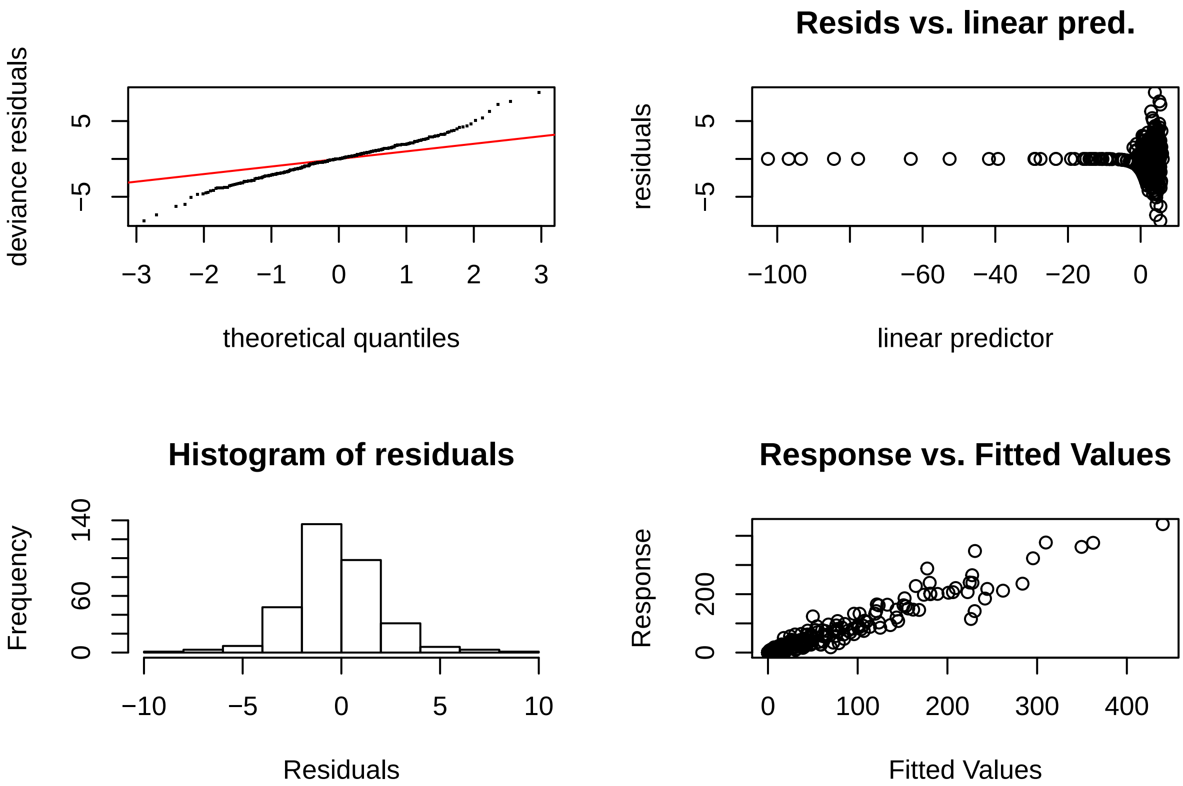
```
## 'data.frame':    334 obs. of  7 variables:
##  $ pollenCount        : int  7 7 2 5 4 0 0 0 13 62 ...
##  $ year               : int  1991 1991 1991 1991 1991 1991 1991 1991 1991 1991 ...
##  $ dayInSeason        : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ temperature        : num  72.4 67.1 68.5 73.4 80.5 ...
##  $ temperatureResidual: num  0.649 -4.796 -3.521 1.207 8.14 ...
##  $ rain               : int  1 0 1 1 1 1 1 1 1 1 ...
##  $ windSpeed          : num  10.4 9.4 8.2 11.8 7.2 7.8 5.4 10.2 5.3 8.8 ...
```

10B

```
fit1 <- mgcv::gam(pollenCount ~ factor(year) + s(dayInSeason, k=27, by=factor(year))
                  + temperatureResidual + rain + s(windSpeed, k=27)
                 , data=ragweed
                 , family=poisson
                   )
```

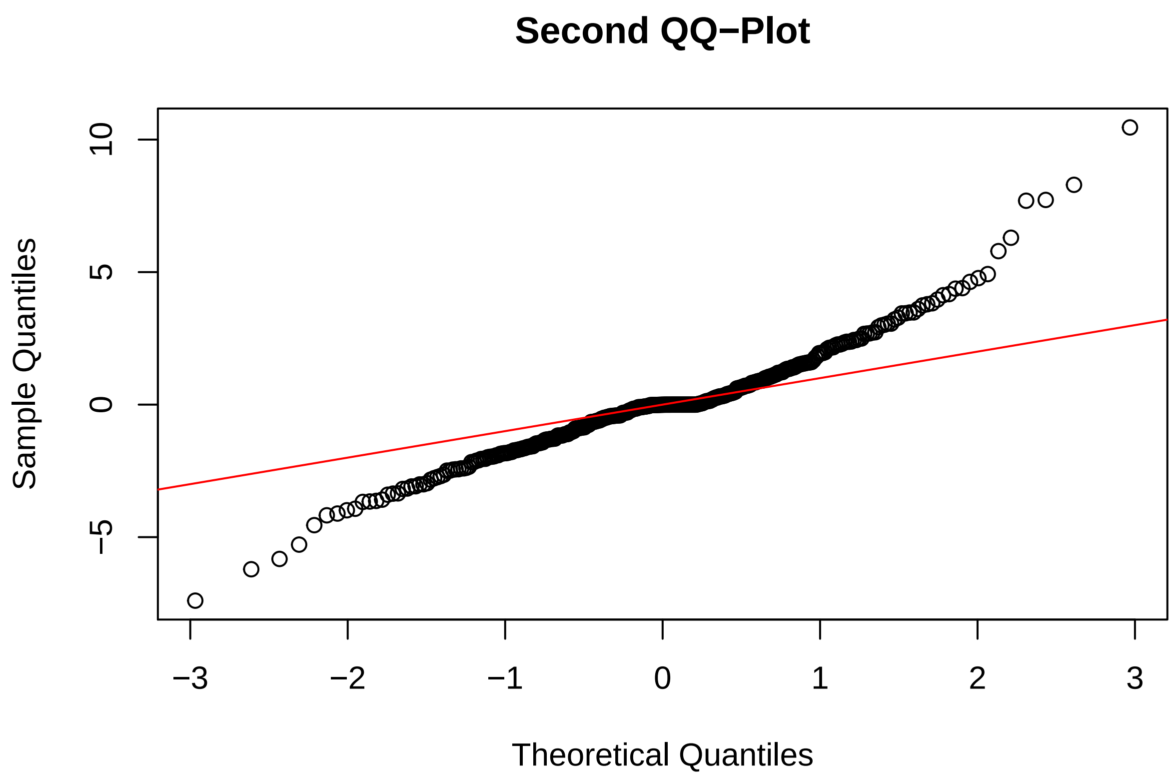
Obtain residual plots for the models.

```
mgcv::gam.check(fit1)
```




```
##
## Method: UBRE   Optimizer: outer newton
## full convergence after 16 iterations.
## Gradient range [-1.343788e-05,9.041719e-07]
## (score 4.452403 & scale 1).
## Hessian positive definite, eigenvalue range [0.0004695876,0.1070234].
## Model rank =  136 / 136
##
## Basis dimension (k) checking results. Low p-value (k-index<1) may
## indicate that k is too low, especially if edf is close to k'.
##
##                                    k'  edf k-index p-value
## s(dayInSeason):factor(year)1991 26.0 25.9    0.92   0.085 .
## s(dayInSeason):factor(year)1992 26.0 22.2    0.92   0.055 .
## s(dayInSeason):factor(year)1993 26.0 24.4    0.92   0.090 .
## s(dayInSeason):factor(year)1994 26.0 22.9    0.92   0.055 .
## s(windSpeed)                    26.0 25.4    1.11   0.980
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
qqnorm(residuals(fit1, type="scaled.pearson"), main="Second QQ-Plot")
abline(0, 1, col="red")
```



10C

Obtain alternative fits.

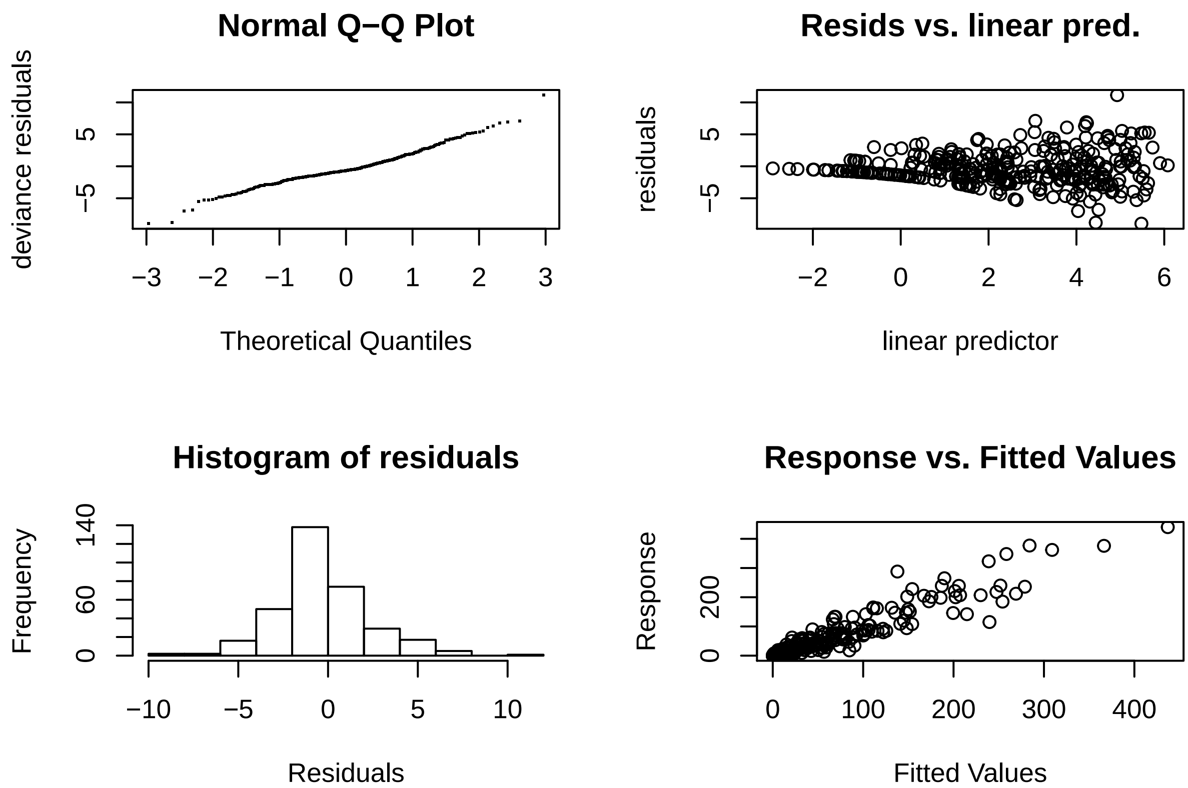
```
# quasipoisson
fit2 <- mgcv::gam(pollenCount ~ factor(year) + s(dayInSeason, k=27, by=factor(year))
                   + temperatureResidual + rain + s(windSpeed, k=27)
                  , data=ragweed
                  , family=quasipoisson
                    )
```

```
# square root variance transformation
fit3 <- mgcv::gam(sqrt(pollenCount) ~ factor(year) + s(dayInSeason, k=27, by=factor(year))
                   + temperatureResidual + rain + s(windSpeed, k=27)
                  , data=ragweed
                  , family=gaussian(link="identity")
                    )
```

10D

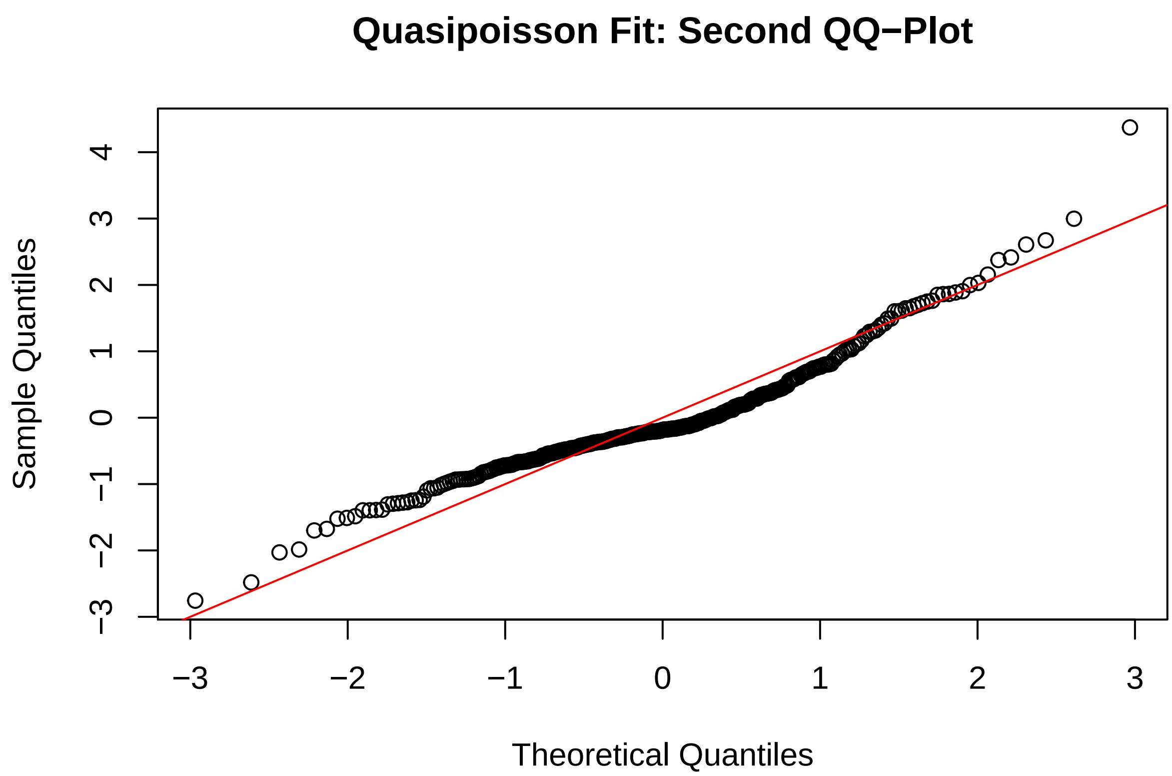
Obtain residual plots for the new fits, analogous to those obtained for fit1 in Part B

```
# quasipoisson
mgcv::gam.check(fit2)
```

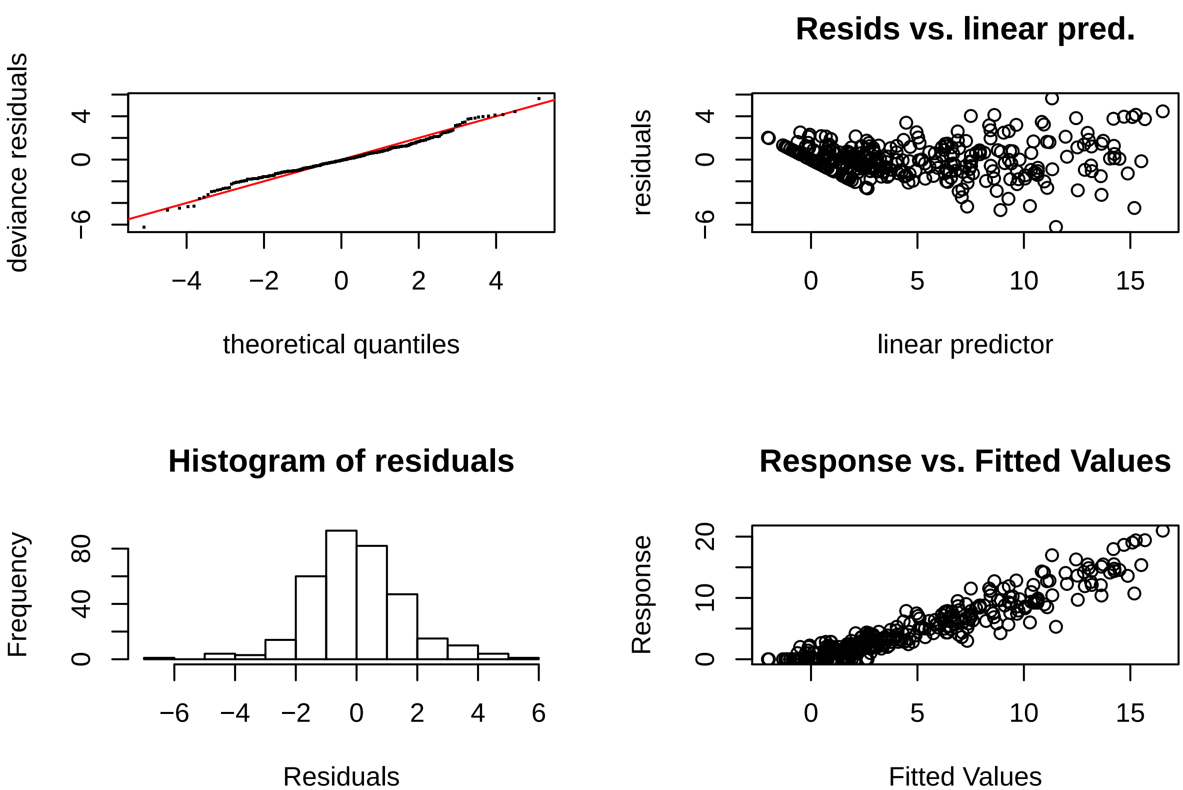



```
##
## Method: GCV   Optimizer: outer newton
## full convergence after 6 iterations.
## Gradient range [-6.282682e-07,3.073244e-05]
## (score 9.597656 & scale 8.54425).
## Hessian positive definite, eigenvalue range [0.01099335,0.05950797].
## Model rank =  136 / 136
##
## Basis dimension (k) checking results. Low p-value (k-index<1) may
## indicate that k is too low, especially if edf is close to k'.
##
##                                    k'   edf k-index p-value
## s(dayInSeason):factor(year)1991 26.00  7.90    0.96    0.32
## s(dayInSeason):factor(year)1992 26.00 11.73    0.96    0.30
## s(dayInSeason):factor(year)1993 26.00  7.67    0.96    0.36
## s(dayInSeason):factor(year)1994 26.00  5.88    0.96    0.35
## s(windSpeed)                    26.00 14.65    1.05    0.86
```

```r
qqnorm(residuals(fit2, type="scaled.pearson")
       , main="Quasipoisson Fit: Second QQ-Plot")
abline(0, 1, col="red")
```



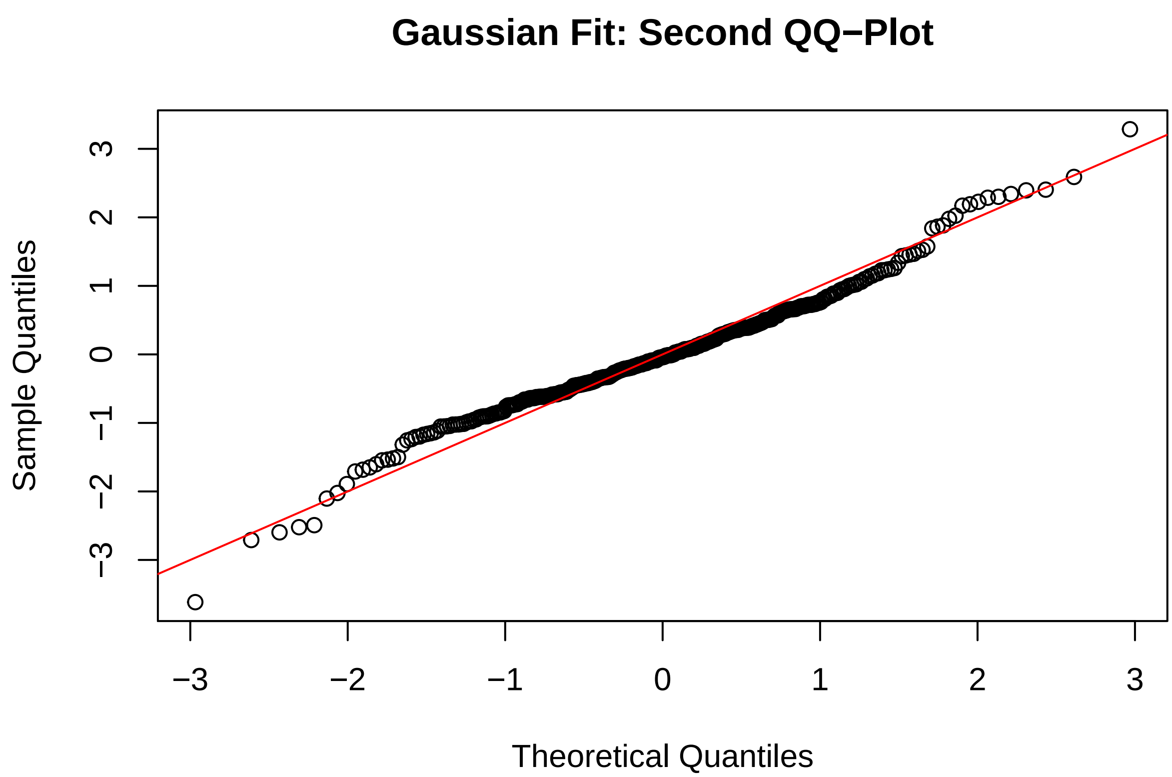

```r
mgcv::gam.check(fit3)
```




```
##
## Method: GCV   Optimizer: magic
## Smoothing parameter selection converged after 7 iterations.
```

```
## The RMS GCV score gradient at convergence was 1.73366e-07 .
## The Hessian was positive definite.
## Model rank =  136 / 136
##
## Basis dimension (k) checking results. Low p-value (k-index<1) may
## indicate that k is too low, especially if edf is close to k'.
##
##                                       k'   edf k-index p-value
## s(dayInSeason):factor(year)1991 26.00 15.23    0.97    0.22
## s(dayInSeason):factor(year)1992 26.00  9.31    0.97    0.24
## s(dayInSeason):factor(year)1993 26.00 10.17    0.97    0.23
## s(dayInSeason):factor(year)1994 26.00  5.69    0.97    0.20
## s(windSpeed)                    26.00  7.80    1.00    0.46
```

```r
qqnorm(residuals(fit3, type="scaled.pearson")
       , main="Gaussian Fit: Second QQ-Plot"
       )
abline(0, 1, col="red")
```



10E

Based on the above summaries, I believe that the Gaussian fit for the square root transformation (fit3) is superior to the Poisson and QuasiPoisson fits. The scaled Pearson residual QQ-Norm plot shows that the Gaussian response distribution seems to result in a superior fit to the data.

```r
# graphical representations are available in the previous question
# numerical summary immediately below.
mgcv::summary.gam(fit3)
```

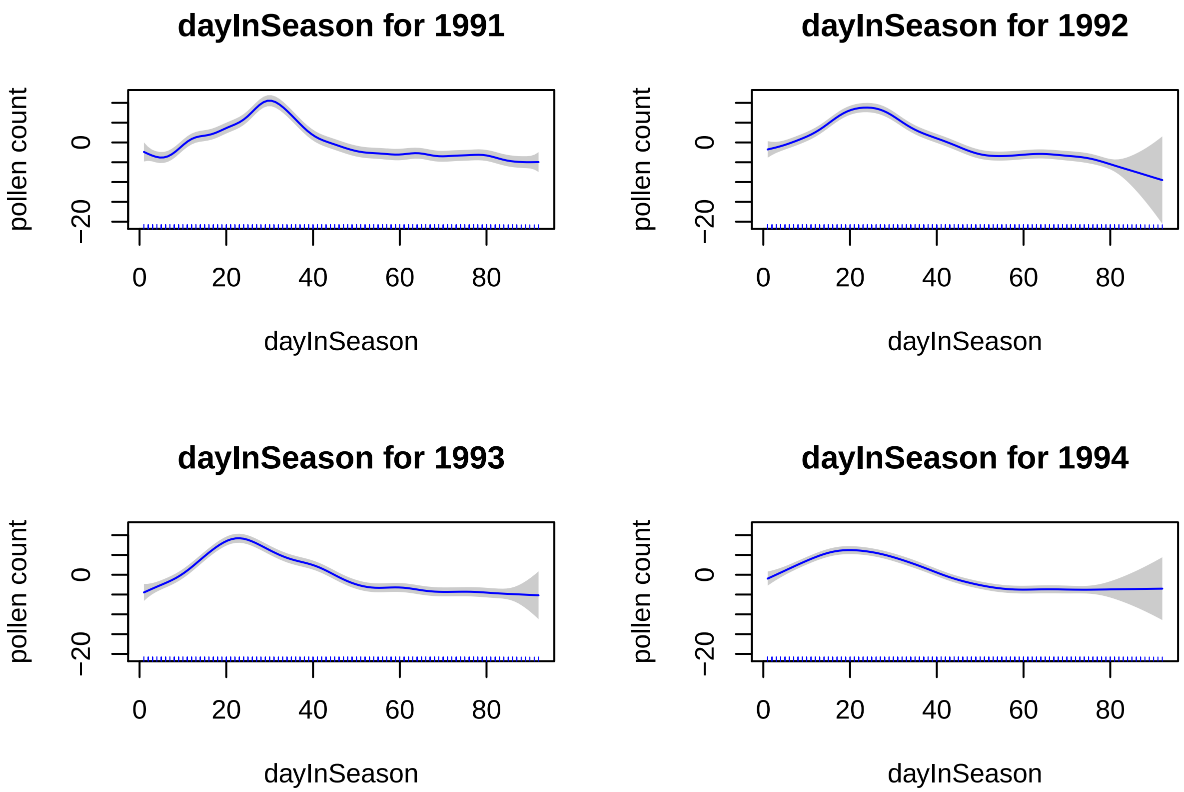
```
##
```

```
## Family: gaussian
## Link function: identity
##
## Formula:
## sqrt(pollenCount) ~ factor(year) + s(dayInSeason, k = 27, by = factor(year)) +
##     temperatureResidual + rain + s(windSpeed, k = 27)
##
## Parametric coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)           3.60601    0.35948  10.031  < 2e-16 ***
## factor(year)1992      0.09090    0.29382   0.309 0.757277
## factor(year)1993     -0.20278    0.26391  -0.768 0.442920
## factor(year)1994     -1.13137    0.31720  -3.567 0.000425 ***
## temperatureResidual   0.10174    0.01902   5.348 1.85e-07 ***
## rain                  1.53507    0.34149   4.495 1.02e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                                   edf Ref.df      F p-value
## s(dayInSeason):factor(year)1991 15.226 18.434 29.971 < 2e-16 ***
## s(dayInSeason):factor(year)1992  9.305 11.504 44.530 < 2e-16 ***
## s(dayInSeason):factor(year)1993 10.170 12.578 48.865 < 2e-16 ***
## s(dayInSeason):factor(year)1994  5.689  7.078 47.483 < 2e-16 ***
## s(windSpeed)                     7.798  9.655  6.015 4.4e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =  0.867   Deviance explained = 88.8%
## GCV = 3.5274  Scale est. = 2.9551    n = 334
```

10F

Show the four penalized spline fits for the effect of dayInSeason on the mean response.

```r
par(mfrow=c(2,2))
plot(fit3, shade=TRUE, col="blue", rug=TRUE, select=c(1)
     , main="dayInSeason for 1991"
     , ylab="pollen count"
     )
plot(fit3, shade=TRUE, col="blue", rug=TRUE, select=c(2)
     , main="dayInSeason for 1992"
     , ylab="pollen count"
     )
plot(fit3, shade=TRUE, col="blue", rug=TRUE, select=c(3)
     , main="dayInSeason for 1993"
     , ylab="pollen count"
     )
plot(fit3, shade=TRUE, col="blue", rug=TRUE, select=c(4)
     , main="dayInSeason for 1994"
     , ylab="pollen count"
     )
```

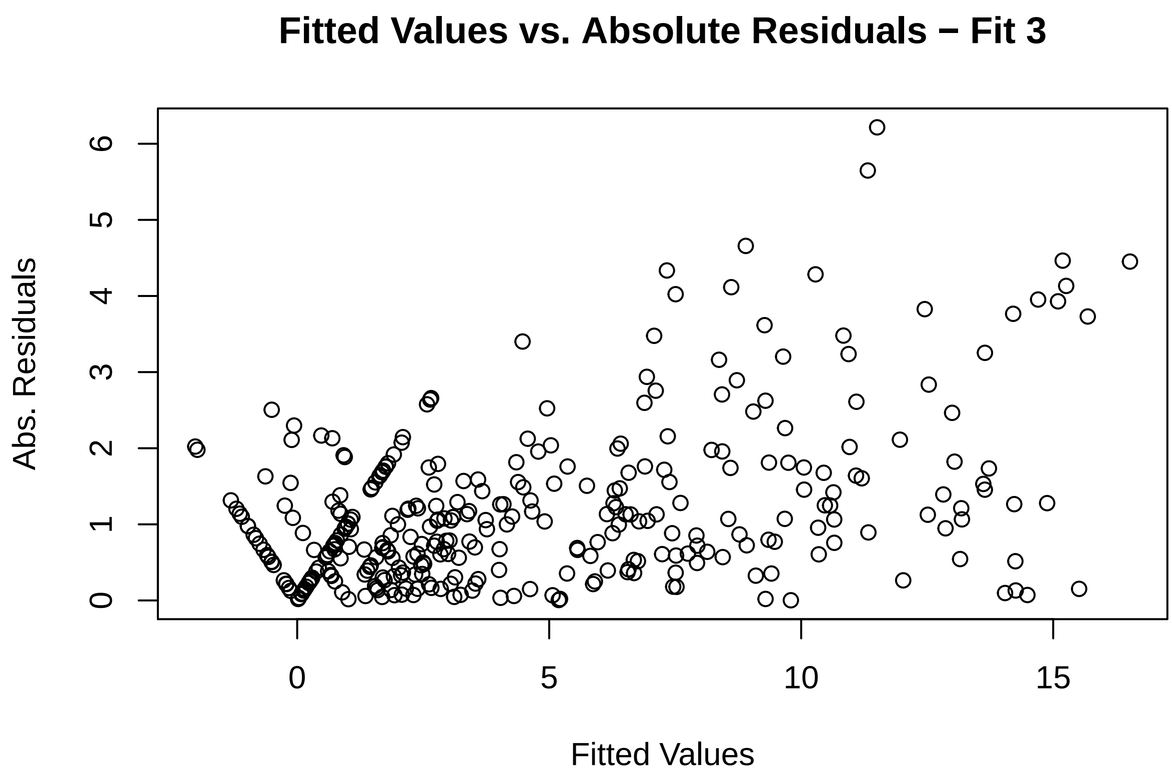



```
par(mfrow=c(1,1))
```

Question 2

For the square root transformation (fit3), see whether the idea of constant variance is reasonable.

```
resid <- abs(residuals(fit3))
fitted <- fitted(fit3)
plot(fitted, resid
     , main="Fitted Values vs. Absolute Residuals - Fit 3"
     , xlab="Fitted Values"
     , ylab="Abs. Residuals"
     )
```



From the above plot, it does not appear that the assumption of constant variance is reasonable. As our fitted values increase, the variance of our absolute residuals increases.

Question 3

From the estimated scale in the QuasiPoisson model, does the scale parameter imply that we may have concern about overdispersion?

```
print("Scale Parameter given by:")
```

```
## [1] "Scale Parameter given by:"
```

```
print(fit2$scale)
```

```
## [1] 8.54425
```

Considering that we are looking for a scale value of 1, I believe we do have legitimate concerns about overdispersion.

Question 4

Test whether the QuasiPoisson fit is statistically significantly different from the Poisson fit.

```
anova(fit1, fit2, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: pollenCount ~ factor(year) + s(dayInSeason, k = 27, by = factor(year)) +
##     temperatureResidual + rain + s(windSpeed, k = 27)
## Model 2: pollenCount ~ factor(year) + s(dayInSeason, k = 27, by = factor(year)) +
```

```
##     temperatureResidual + rain + s(windSpeed, k = 27)
##   Resid. Df Resid. Dev      Df Deviance  Pr(>Chi)
## 1    205.43     1567.6
## 2    269.68     2255.5 -64.248  -687.93 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

It appears that we have statistically significant differences between the Poisson and QuasiPoisson fits. The QuasiPoisson is preferable in this case.

Question 5

In the Poisson fit, is there evidence that there is a year by dayInSeason interaction?

```r
mgcv::summary.gam(fit1)
```

```
##
## Family: poisson
## Link function: log
##
## Formula:
## pollenCount ~ factor(year) + s(dayInSeason, k = 27, by = factor(year)) +
##     temperatureResidual + rain + s(windSpeed, k = 27)
##
## Parametric coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)           1.797350   0.083186  21.606   <2e-16 ***
## factor(year)1992     -2.939237  19.585504  -0.150   0.8807
## factor(year)1993     -1.422070   0.633147  -2.246   0.0247 *
## factor(year)1994    -44.641947  74.797144  -0.597   0.5506
## temperatureResidual   0.054357   0.004504  12.068   <2e-16 ***
## rain                  0.819443   0.059913  13.677   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                                 edf Ref.df Chi.sq p-value
## s(dayInSeason):factor(year)1991 25.89  25.99 3287.6  <2e-16 ***
## s(dayInSeason):factor(year)1992 22.23  22.48 2343.0  <2e-16 ***
## s(dayInSeason):factor(year)1993 24.37  24.95 2439.6  <2e-16 ***
## s(dayInSeason):factor(year)1994 22.87  23.21 1103.9  <2e-16 ***
## s(windSpeed)                    25.40  25.94  711.1  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =  0.888   Deviance explained = 94.6%
## UBRE = 4.4524  Scale est. = 1         n = 334
```

From the above output, it appears that we have a significant interaction between the year and dayInSeason variables.

We can also create similar model that does not have the interaction, and test them against each other.

```r
smaller_fit1 <- mgcv::gam(pollenCount ~ factor(year) + s(dayInSeason, k=27)
                  + temperatureResidual + rain + s(windSpeed, k=27)
```

```
                 , data=ragweed
                 , family=poisson
                   )
anova(fit1, smaller_fit1, test="Chisq")
```

```
## Analysis of Deviance Table
##
## Model 1: pollenCount ~ factor(year) + s(dayInSeason, k = 27, by = factor(year)) +
##     temperatureResidual + rain + s(windSpeed, k = 27)
## Model 2: pollenCount ~ factor(year) + s(dayInSeason, k = 27) + temperatureResidual +
##     rain + s(windSpeed, k = 27)
##   Resid. Df Resid. Dev      Df Deviance  Pr(>Chi)
## 1    205.43     1567.6
## 2    276.14     3470.8 -70.717  -1903.2 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Both evaluations suggest significant evidence of a year by dayInSeason interaction.

Question 6

Remove the interaction from the model, still doing the quasipoisson; do a stepwise regression - which model is seleted?

```
detach("package:mgcv", unload=TRUE)
library("gam")
```

```
## Warning: namespace 'mgcv' is not available and has been replaced
## by .GlobalEnv when processing object 'call.'

## Warning: namespace 'mgcv' is not available and has been replaced
## by .GlobalEnv when processing object 'call.'

## Warning: namespace 'mgcv' is not available and has been replaced
## by .GlobalEnv when processing object 'call.'
```

For the following, the quasipoisson response distribution appears to be incompatible with the step.gam function. I use poisson and gaussian response distributions for model selection.

```
pois_init <- gam::gam(pollenCount ~ factor(year) + dayInSeason
                  + temperatureResidual + rain + windSpeed
                 , data=ragweed
                 , family=poisson(link="log")
                   )



pois_step <- gam::step.gam(pois_init, scope=list(
                        "year" = ~1 + year
                        , "dayInSeason" = ~1 + dayInSeason + s(dayInSeason, 2)
                        , "temperatureResidual" = ~1 + temperatureResidual
                        , "rain" = ~1 + rain
                        , "windSpeed" = ~1 + windSpeed + s(windSpeed, 2)
                        )
                          )
```

```
## Start:  pollenCount ~ factor(year) + dayInSeason + temperatureResidual +      rain + windSpeed; AIC=
```

```
## Warning: namespace 'mgcv' is not available and has been replaced
## by .GlobalEnv when processing object 'call.'
```

```
## Step:1 pollenCount ~ factor(year) + s(dayInSeason, 2) + temperatureResidual +      rain + windSpeed
## Step:2 pollenCount ~ factor(year) + s(dayInSeason, 2) + temperatureResidual +      rain + s(windSpee
```

```
gauss_init <- gam::gam(sqrt(pollenCount) ~ factor(year) + dayInSeason
                  + temperatureResidual + rain + windSpeed
                 , data=ragweed
                 , family=gaussian(link="identity")
                   )


gauss_step <- gam::step.gam(gauss_init, scope=list(
                       "year" = ~1 + year
                       , "dayInSeason" = ~1 + dayInSeason + s(dayInSeason, 2)
                       , "temperatureResidual" = ~1 + temperatureResidual
                       , "rain" = ~1 + rain
                       , "windSpeed" = ~1 + windSpeed + s(windSpeed, 2)
                       )
                         )
```

```
## Start:  sqrt(pollenCount) ~ factor(year) + dayInSeason + temperatureResidual +      rain + windSpeed
## Step:1 sqrt(pollenCount) ~ factor(year) + s(dayInSeason, 2) + temperatureResidual +      rain + windS
```

Both GLMs result in the same model:

```
names(gauss_step$model)[-1]
```

```
## [1] "factor(year)"        "s(dayInSeason, 2)"   "temperatureResidual"
## [4] "rain"                "windSpeed"
```

Question 7

Fit a model using cosso. COSSO does not have the Poisson or QuasiPoisson response distributions available, so I will use Guassian and transform the response in some of the models.

```
Y <- ragweed$pollenCount
Y_alt <- log(ragweed$pollenCount)
Y_alt2 <- sqrt(ragweed$pollenCount)
X <- ragweed[, c(2, 3, 5, 6, 7)]
# make sure everything is in 'integer format'
X$temperatureResidual <- as.integer(X$temperatureResidual)
X$windSpeed <- as.integer(X$windSpeed)
str(X)
```

```
## 'data.frame':    334 obs. of  5 variables:
##  $ year               : int  1991 1991 1991 1991 1991 1991 1991 1991 1991 1991 ...
##  $ dayInSeason        : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ temperatureResidual: int  0 -4 -3 1 8 8 1 -2 -5 -1 ...
##  $ rain               : int  1 0 1 1 1 1 1 1 1 1 ...
##  $ windSpeed          : int  10 9 8 11 7 7 5 10 5 8 ...
```

```
cosso_mod1 <- cosso::cosso(x=X, y=Y, family="Gaussian")
```

```
## Error in solve.default(A + 1e-07 * diag(nrow(A)), b): system is computationally singular: reciprocal
```

```r
cosso_mod2 <- cosso::cosso(x=X, y=Y_alt, family="Gaussian")
```

```
## Error in solve.default(A + 1e-07 * diag(nrow(A)), b): system is computationally singular: reciprocal
```

```r
cosso_mod3 <- cosso::cosso(x=X, y=Y_alt2, family="Gaussian")
```

```
## Error in solve.default(A + 1e-07 * diag(nrow(A)), b): system is computationally singular: reciprocal
```

None of the cosso models were able to run successfully.