Final Project: Music v. Mental Health

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Distribution Report:

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Introduction

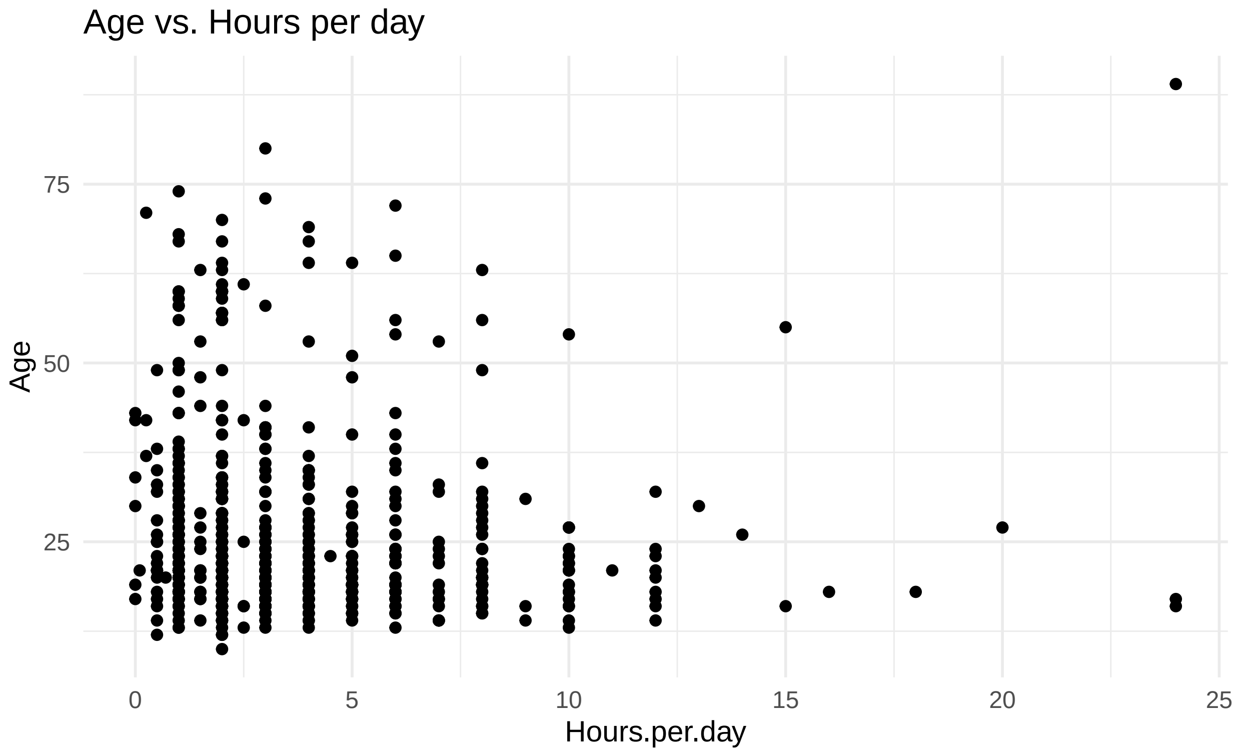
In this project, we will investigate the relationship between how many hours per day someone listens to music (our response variable) and their age and mental health. To do this, we used data collected from a music and mental health survey.

Making categories for Anxiety, Depression, and Insomnia

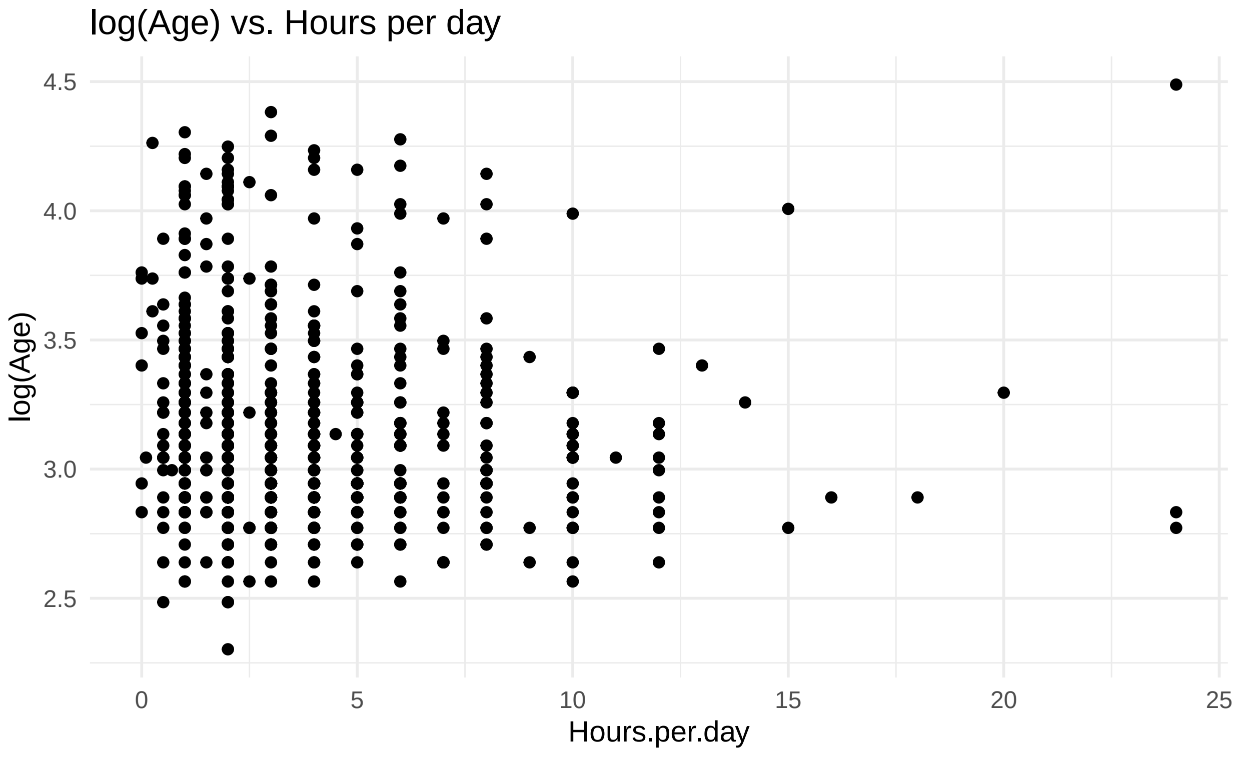
Since our data had people rate their anxiety, depression, and insomnia on a scale of 1 to 10 (only integers), we will make categories for `Anxiety`, `Depression`, and `Insomnia` so that the categories will be binary. For example, for `Anxiety`, we will have a category called `Anxious` that is 1 if `Anxiety` $>$ 5 and 0 otherwise.

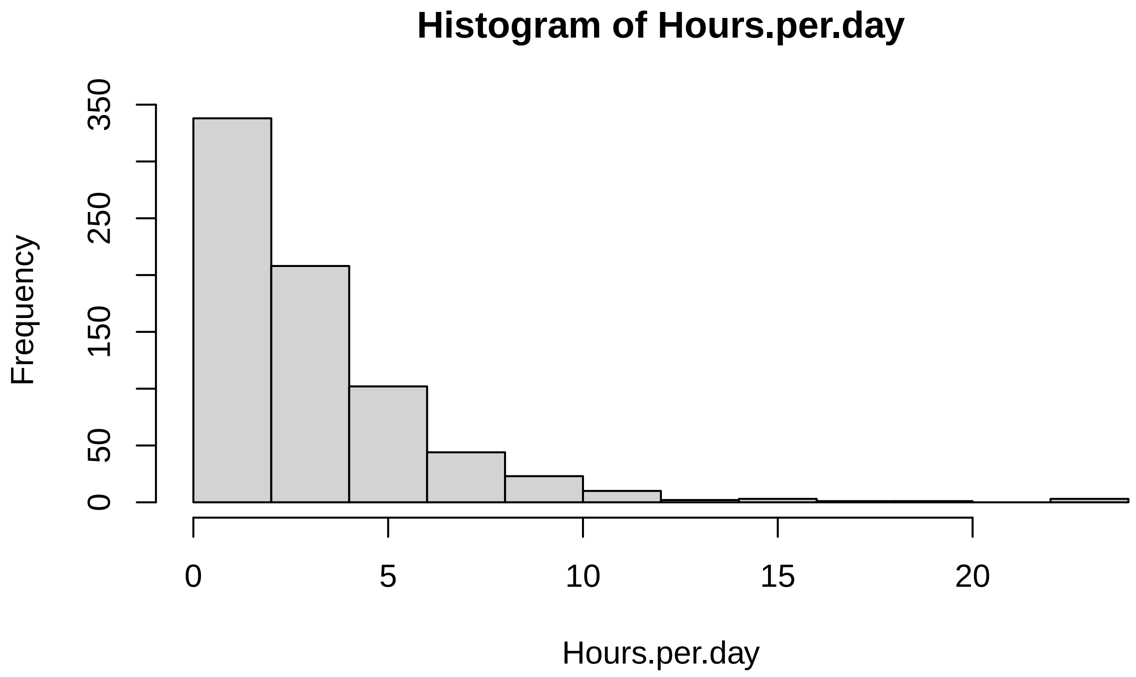
Testing Non-linearity

We don't need to test for non-linearity for categorical variables so we will only test for non-linearity for the continuous variables, namely age.



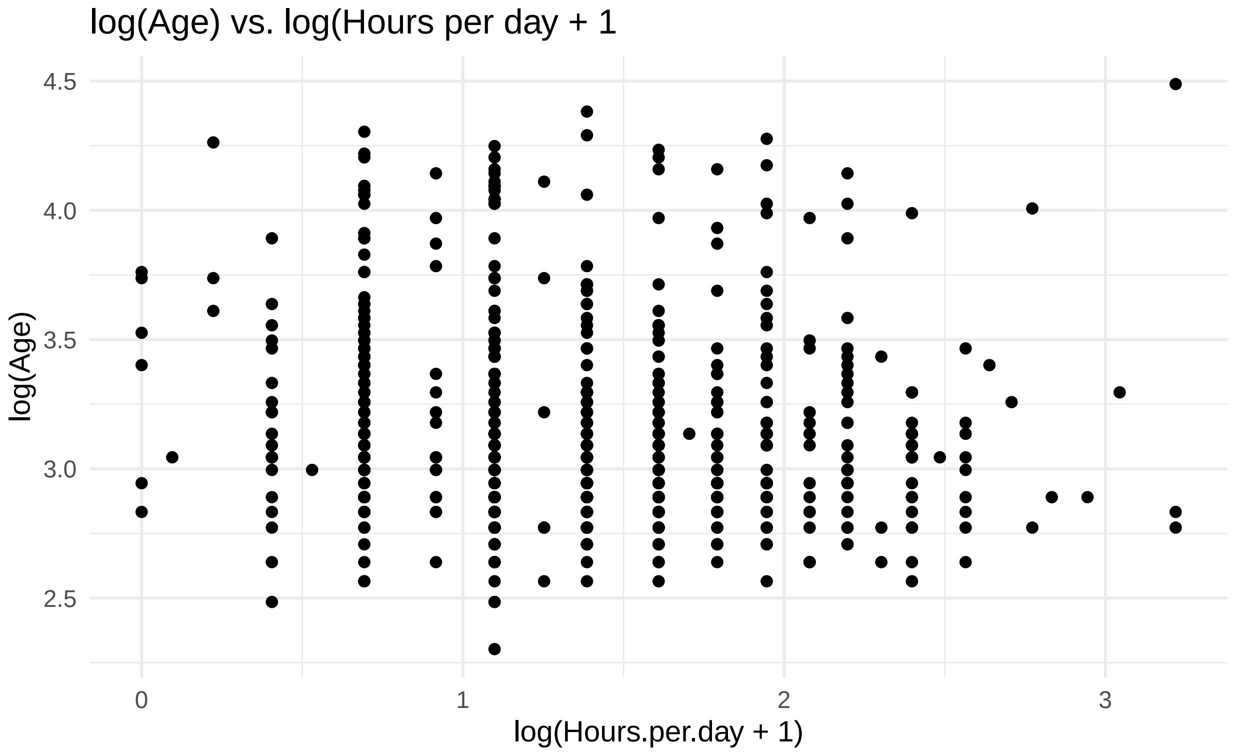
There doesn't seem to be a linear relationship between age and hours per day. We can transform age by logging it so that the relationship looks less non-linear. With log age:





Since the hours per day that people listen to music is not normally distributed, for each of the models, we will have a model where we log Hours.per.day and a model where we fit it to a log-link Gamma distribution.

Also, since half our models will have log Hours.per.day, we check if the relationship with log(Age) and log(Hours.per.day + 1) is linear.

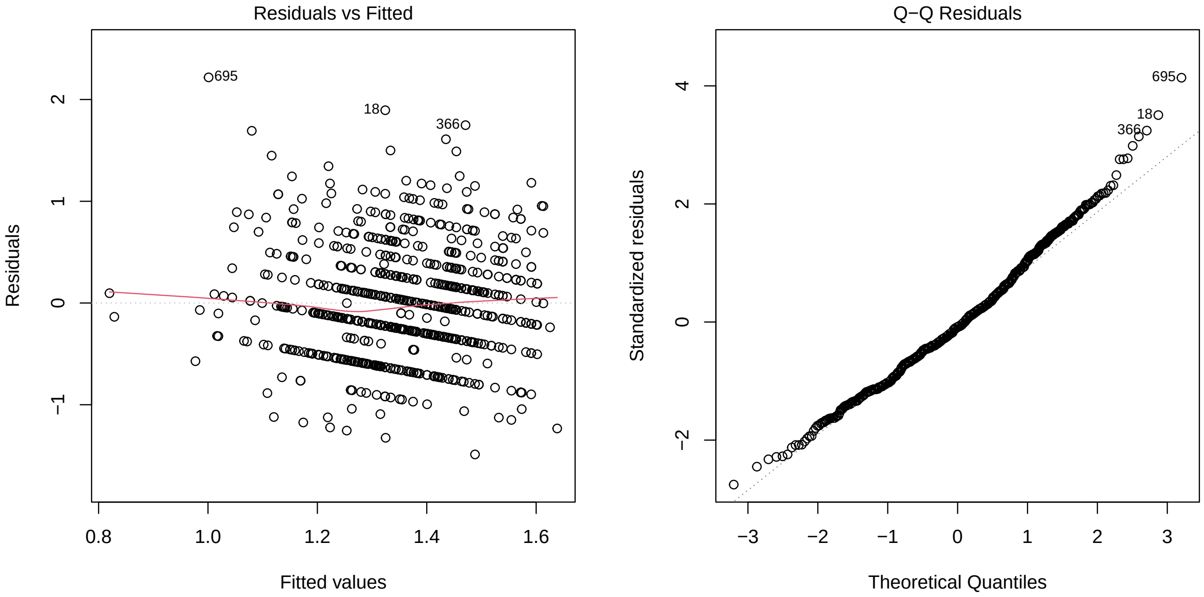


The relationship between log(Age) and log(Hours.per.day + 1) is not obviously non-linear, so we can use log(Age) in the linear model with log(Hours.per.day + 1).

Fitted models

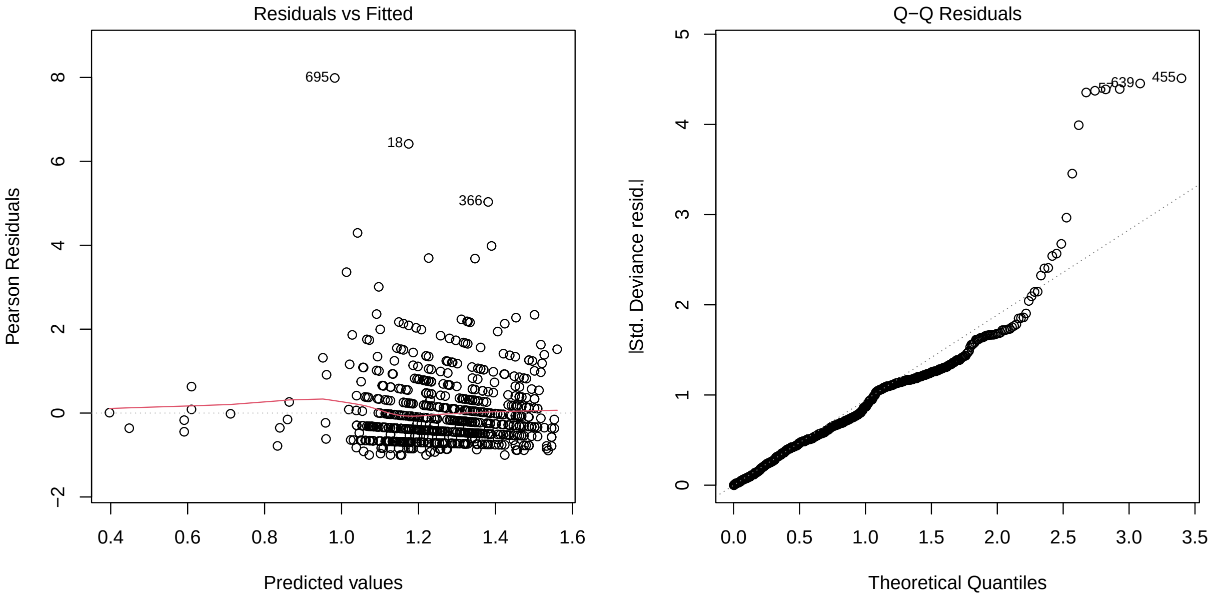
For fitA, which will have a log model, `fitAlog`, and a gamma generalized linear model (glm), `fitAgamma`, with covariates `log(Age)`,`Anxious`, `Depressed`, `Insomniac`, and `Music.effects`.
`Anxious`, `Depressed`, and `Insomniac` are the binary categories we made earlier.
`Music.effects` is a categorical variable where people reported what effect they felt music had on their mental health. The categories for `Music.effects` are `Improve`, `No effect`, and `Worsen`.

```
##
## Call:
## lm(formula = log(Hours.per.day + 1) ~ log(Age) + Anxious + Depressed +
##     Insomniac + Music.effects)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.48822 -0.35553 -0.04605  0.33077  2.21770
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)             1.51836    0.26176   5.801 9.85e-09 ***
## log(Age)               -0.16400    0.05365  -3.057  0.00232 **
## Anxious                -0.01895    0.04460  -0.425  0.67113
## Depressed               0.13938    0.04408   3.162  0.00163 **
## Insomniac               0.11785    0.04492   2.624  0.00888 **
## Music.effectsImprove    0.28938    0.19371   1.494  0.13565
## Music.effectsNo effect  0.21897    0.19647   1.115  0.26543
## Music.effectsWorsen    -0.02302    0.23368  -0.099  0.92156
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
##
## Residual standard error: 0.5422 on 727 degrees of freedom
## Multiple R-squared:  0.05533,    Adjusted R-squared:  0.04623
## F-statistic: 6.083 on 7 and 727 DF,  p-value: 6.435e-07
```



```
##
## Call:
## glm(formula = Hours.per.day + 0.001 ~ log(Age) + Anxious + Depressed +
##     Insomniac + Music.effects, family = Gamma(link = "log"))
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)             0.96570    0.41641   2.319   0.0207 *
## log(Age)               -0.12309    0.08535  -1.442   0.1497
## Anxious                -0.05890    0.07096  -0.830   0.4068
## Depressed               0.17935    0.07013   2.558   0.0107 *
## Insomniac               0.14014    0.07146   1.961   0.0502 .
## Music.effectsImprove    0.61635    0.30816   2.000   0.0459 *
## Music.effectsNo effect  0.56906    0.31255   1.821   0.0691 .
## Music.effectsWorsen     0.30143    0.37173   0.811   0.4177
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
##
## (Dispersion parameter for Gamma family taken to be 0.7440657)
##
```

```
##     Null deviance: 503.18  on 734  degrees of freedom
## Residual deviance: 486.59  on 727  degrees of freedom
## AIC: 3250.1
##
## Number of Fisher Scoring iterations: 7
```



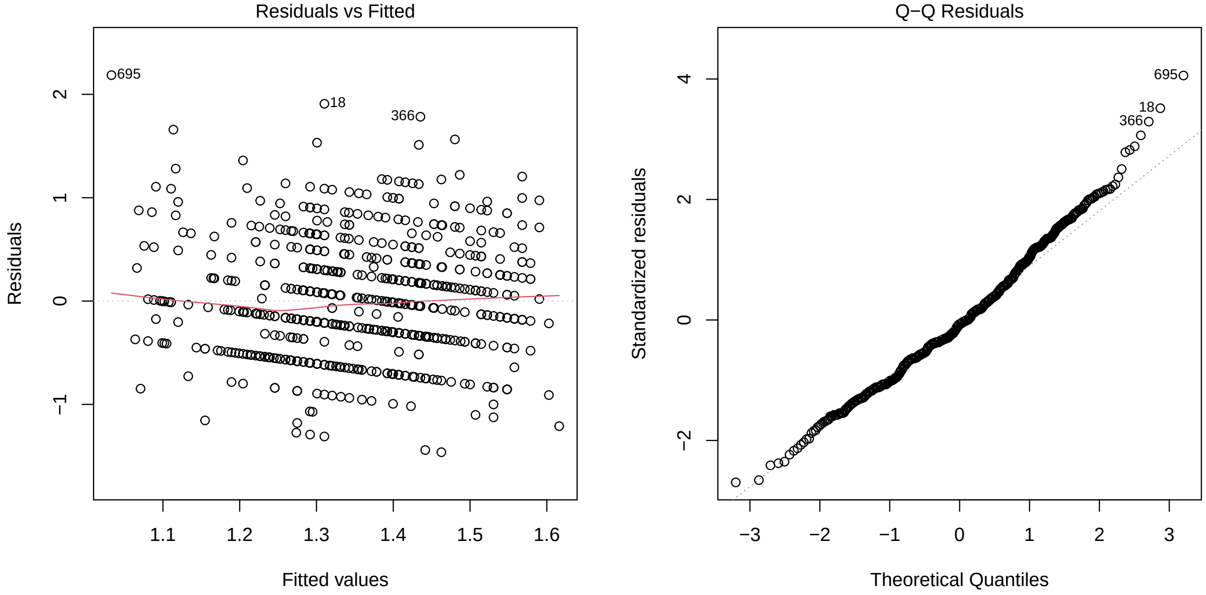
Analysis:

- For Log: From looking at the Residual Vs Fitted plot for `fitAlog`, it seems that the normality assumption is not violated because the shape of the fit is cloud-like without any noticeable pattern. This means that `fitAlog` does have constant variance. However, there are possible outliers such as point 696 or 19. For the Normal Q-Q plot, normality doesn't seem to be violated because most error points remains on the normality line. Nevertheless, there are still evidences of outliers.
- For Gamma: Since the distribution is Gamma, it is possible to observe clustering of negatively valued residuals in Residuals and Fitted. This means that `fitAgamma`, doesn't seem to violate normality assumption. In another word, `fitAgamma` have a constant Variance. However, there are possible outliers such as points 696 or 19. For the Normal Q-Q plot, Gamma violated normality assumption, as errors points are going off the normal line.

For the fitB's, `fitBlog` and `fitBgamma`, we used only the covariates that were individually significant in `fitA` and `fitAgamma`. As a result, the covariates for `fitBlog` and `fitBgamma` are `log(Age)`, `Depressed`, and `Insomniac`.

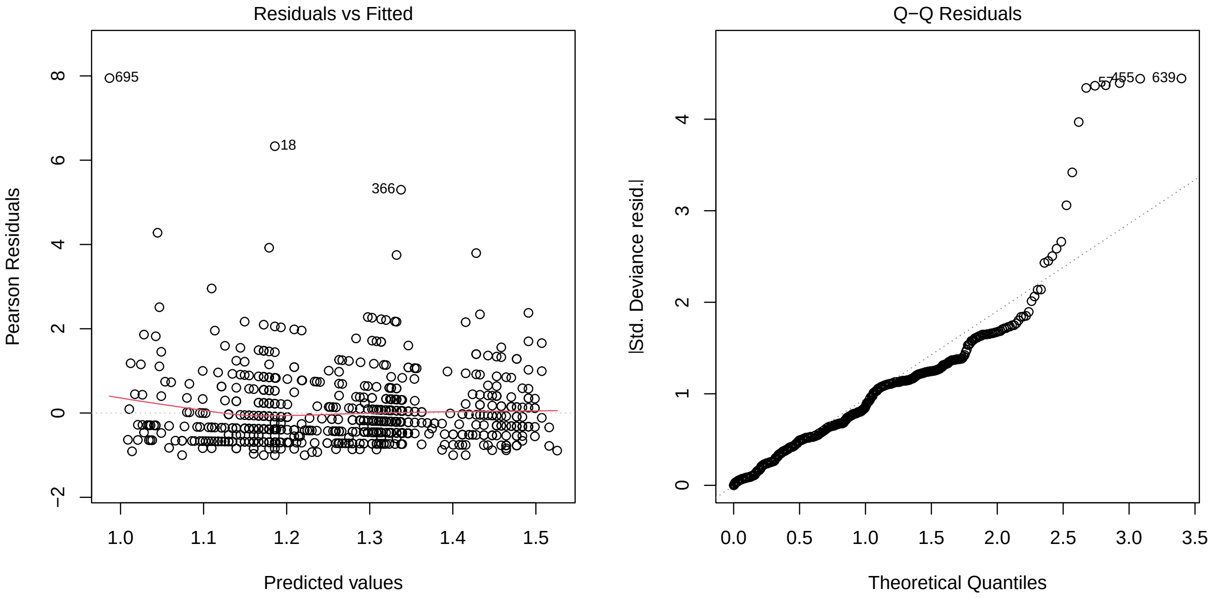
```
##
## Call:
## lm(formula = log(Hours.per.day + 1) ~ log(Age) + Depressed +
##     Insomniac)
##
## Residuals:
```

```
##      Min       1Q   Median       3Q      Max 
## -1.46264 -0.34592 -0.03795  0.32323  2.18588 
## 
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept)  1.78490    0.17085  10.447  < 2e-16 ***
## log(Age)    -0.16751    0.05327  -3.145  0.00173 ** 
## Depressed    0.13257    0.04175   3.175  0.00156 ** 
## Insomniac    0.11492    0.04479   2.566  0.01050 *  
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 0.5441 on 731 degrees of freedom
## Multiple R-squared:  0.04363,    Adjusted R-squared:  0.0397 
## F-statistic: 11.12 on 3 and 731 DF,  p-value: 3.851e-07
```



```
## 
## Call:
## glm(formula = Hours.per.day + 0.001 ~ log(Age) + Depressed + 
##     Insomniac, family = Gamma(link = "log"))
## 
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept)  1.52650    0.27113   5.630 2.57e-08 ***
## log(Age)    -0.12026    0.08453  -1.423   0.1553    
## Depressed    0.15340    0.06626   2.315   0.0209 *  
## Insomniac    0.14463    0.07108   2.035   0.0422 *  
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
```

```
## (Dispersion parameter for Gamma family taken to be 0.7455182)
##
##     Null deviance: 503.18  on 734  degrees of freedom
## Residual deviance: 490.98  on 731  degrees of freedom
## AIC: 3249.4
##
## Number of Fisher Scoring iterations: 6
```



Analysis:

- For Log: From looking at the Residual Vs Fitted plot for `fitBlog`, it seems that the normality assumption is not violated because the shape of the fit is cloud-like without any noticeable pattern. This means that `fitBlog` does have constant variance. However, there are possible outliers such as point 696 or 19. For the Normal Q-Q plot, normality doesn't seem to be violated because most error points remains on the normality line. Nevertheless, there are still evidences of outliers.
- For Gamma: Since the distribution is Gamma, it is possible to observe clustering of negatively valued residuals in Residuals and Fitted. This means that `fitBgamma`, doesn't seem to violate normality assumption. In another word, `fitAgamma` have a constant Variance. However, there are possible outliers such as points 696 or 19. For the Normal Q-Q plot, Gamma violated normality assumption, as errors points are going off the normal line.

AIC

AIC(fitAlog) = 1196.0682801
AIC(fitBlog) = 1197.1126943

AIC(fitAgamma) = 3250.087381
AIC(fitBgamma) = 3249.3800894

BIC

BIC(fitAlog) = 1237.4671146
BIC(fitBlog) = 1220.1120468

BIC(fitAgamma) = 3291.4862155
BIC(fitBgamma) = 3272.3794419

AIC and BIC analysis

`fitAlog` is a better fit than `fitBlog` according to AIC because it has a lower AIC. `fitBlog` is a better fit than `fitAlog` according to BIC because it has a lower BIC.

`fitAgamma` is a better fit than `fitBgamma` according to AIC because it has a lower AIC. `fitBgamma` is a better fit than `fitAgamma` according to BIC because it has a lower BIC.

Since which model is better according to AIC and BIC is different, we can use either fitA or fitB. One isn’t clearly better than the other. We can confirm this with anova tests.

ANOVA F-Tests

```
## ANOVA tests

anova(fitAlog, fitBlog)
```

```
## Analysis of Variance Table
##
## Model 1: log(Hours.per.day + 1) ~ log(Age) + Anxious + Depressed + Insomniac +
##     Music.effects
## Model 2: log(Hours.per.day + 1) ~ log(Age) + Depressed + Insomniac
##   Res.Df    RSS Df Sum of Sq      F  Pr(>F)
## 1    727 213.75
## 2    731 216.40 -4   -2.6465 2.2503 0.06215 .
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
```

The null hypothesis H_0: $\beta_2 = \beta_5 = 0$ vs. H_1: $\beta_2 \neq 0$ or $\beta_2 \neq 0$. We fail to reject the null because the $Pr(> F) = 0.06215 > \alpha = 0.05$. As a result, fitAlog and fitBlog are the same so we will use the smaller model, fitBlog.

```
anova(fitAgamma, fitBgamma)
```

```
## Analysis of Deviance Table
##
## Model 1: Hours.per.day + 0.001 ~ log(Age) + Anxious + Depressed + Insomniac +
##     Music.effects
## Model 2: Hours.per.day + 0.001 ~ log(Age) + Depressed + Insomniac
##   Resid. Df Resid. Dev Df Deviance
## 1       727     486.59
## 2       731     490.98 -4  -4.3822
```

The deviance is negative, likely because `fitAgamma` and `fitBgamma` violated normality assumptions. We can't reject the null hypothesis if deviance is negative since we can think of it as though deviance is 0. As a result, `fitAgamma` and `fitBgamma` are the same and we will usually choose the smaller model. However, since `fitAgamma` and `fitBgamma` violate normality assumptions, neither of them will be used for our final model.

Interpretation of the final model

Since the gamma distributions violate normality, we would prefer to not use them for our final model. Based on the AIC, BIC, and ANOVA models which show us that `fitAlog` and `fitBlog` are about the same, we will use the smaller model for our final model. As a result, our final model is `fitBlog`, which is: $log(Hours.per.day + 1) = 1.785 - 0.168 log(Age) + 0.133 Depressed + 0.115 Insomniac$

According to `fitBlog`: If log(Age) increase by 1 unit then log(Hours.per.day + 1) will decrease by 0.168 units. If a person ranks their Depression above 5 on a scale from 1 to 10, then log(Hours.per.day + 1) will increase by 0.133 units. If a person ranks their Insomnia above 5 on a scale from 1 to 10, then log(Hours.per.day + 1) will increase by 0.115 units.

One thing to note for our models is that our R^2's were low, including `fitBlog`, which adjusted $R^2 = 0.0397$. We realize this means that our models, including `fitBlog`, explain very little variation in the response (transformed hours per day).

Discussion

In our project, we faced a few minor setbacks. For example, our dataset contained a notable amount of missing values (NA), requiring us to remove rows to ensure accurate calculations for AIC, BIC, and ANOVA. By removing only a small portion of the data, we understand that it could have potentially affected our calculation.

Another difficulty we encountered was the large amount of categorical variables in our dataset. While categorical variables are useful and we did use many in our model, more quantitative variables would be helpful.

Finally, we attempted to find predicted MSE by using LOOCV and kfoldCV to further support the best-fit model argument. However, despite consulting the TA, we continuously encountered errors indicating differences in variable sizes. Ultimately, we decided that since we already have results from ANOVA, AIC and BIC, it is not worth continuing to debug. We firmly believe that the MSE results would align with our other tests, supporting that fitBlog is our best model.

Conclusion

Overall, we decide that `fitBlog` is the best model out of the four we made because it does best to capture the relationship between Hour Per Day with Age and Mental Health.

This project have inspire a possible future study ideas where we utilize the many music genre variables that our dataset and possibly investigate how different music genre affect mental health.

Appendix: R Script

```r
knitr::opts_chunk$set(echo = TRUE, warning = FALSE, fig.align='center')

## Libraries

require('tidyr')
require('dplyr')
require('ggplot2')

## Importing the dataset

data <- read.csv('C:/Users/karen/Documents/STA141A/mxmh_survey_results.csv')
data <- data %>% drop_na(Hours.per.day, Age, Anxiety, Depression, Insomnia, Music.effects)
attach(data)
head(data)

## Making (binary) categories

# mark people as anxious (1) if anxiety > 5, not anxious (0) otherwise
data$Anxious = ifelse(Anxiety > 5, 1, 0)
# mark people as depressed (1) if depression > 5, not depressed (0) otherwise
data$Depressed = ifelse(Depression > 5, 1, 0)
# mark people as insomniac (1) if insomnia > 5, not insomniac (0) otherwise
data$Insomniac = ifelse(Insomnia > 5, 1, 0)

head(data)
attach(data)

## Plots

ggplot(pivot_longer(data = data, 2), aes(Hours.per.day, Age)) +
  labs(title = 'Age vs. Hours per day') +
  theme_minimal() + geom_point()

# log transform because there are a few high values and many low values
ggplot(pivot_longer(data = data, 2), aes(Hours.per.day, log(Age))) +
  labs(title = 'log(Age) vs. Hours per day') +
  theme_minimal() + geom_point()

hist(Hours.per.day)
# Hours per day is not normal so we can log transform it or use gamma glm

# log transform because there are a few high values and many low values
ggplot(pivot_longer(data = data, 2), aes(log(Hours.per.day + 1), log(Age))) +
  labs(title = 'log(Age) vs. log(Hours per day + 1') +
  theme_minimal() + geom_point()

## Fits

# fitA where we log Hours.per.day + 1 since Hours.per.day is not normally distributed.
fitAlog <- lm(log(Hours.per.day + 1) ~ log(Age) + Anxious + Depressed + Insomniac + Music.effects)
summary(fitAlog)
```

```
# Residuals vs. Fitted Values Plot and QQ Plot
par(mfrow = c(1,2))
plot(fitAlog, which = c(1,2))

# fitA where it's fitted to a gamma distribution
# For both fitAlog and fitAgamma, we add 1 to Hours.per.day because we can't log zero.
fitAgamma <- glm(Hours.per.day + 0.001 ~ log(Age) + Anxious + Depressed + Insomniac + Music.effects,
                 family = Gamma (link = 'log'))
summary(fitAgamma)

# Residuals vs. Fitted Values Plot and QQ Plot
par(mfrow = c(1,2))
plot(fitAgamma, which = c(1,2))

# log Hours.per.day +1
fitBlog <- lm(log(Hours.per.day + 1) ~ log(Age) + Depressed + Insomniac)
summary(fitBlog)

# Residuals vs. Fitted Values Plot and QQ Plot
par(mfrow = c(1,2))
plot(fitBlog, which = c(1,2))

# gamma glm
fitBgamma <- glm(Hours.per.day + 0.001 ~ log(Age) + Depressed + Insomniac,
                 family = Gamma (link = 'log'))
summary(fitBgamma)

# Residuals vs. Fitted Values Plot and QQ Plot
par(mfrow = c(1,2))
plot(fitBgamma, which = c(1,2))

##AIC

AIC(fitAlog)
AIC(fitBlog)

AIC(fitAgamma)
AIC(fitBgamma)

## BIC

BIC(fitAlog)
BIC(fitBlog)

BIC(fitAgamma)
BIC(fitBgamma)

## ANOVA tests

anova(fitAlog, fitBlog)

anova(fitAgamma, fitBgamma)
```