

# Statistics 135 – Lab Project

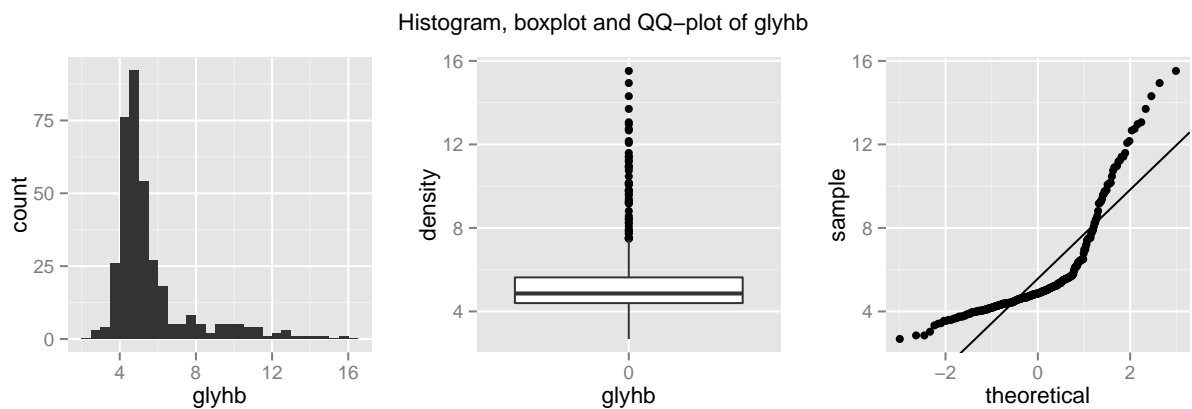
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## 1 Background

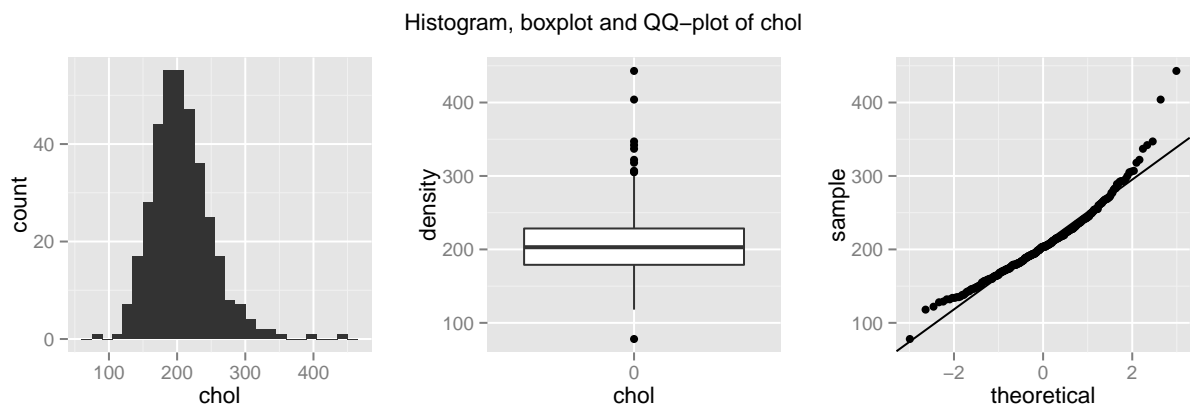
## 2 Accessing Data, Visualization and Summarization

1.



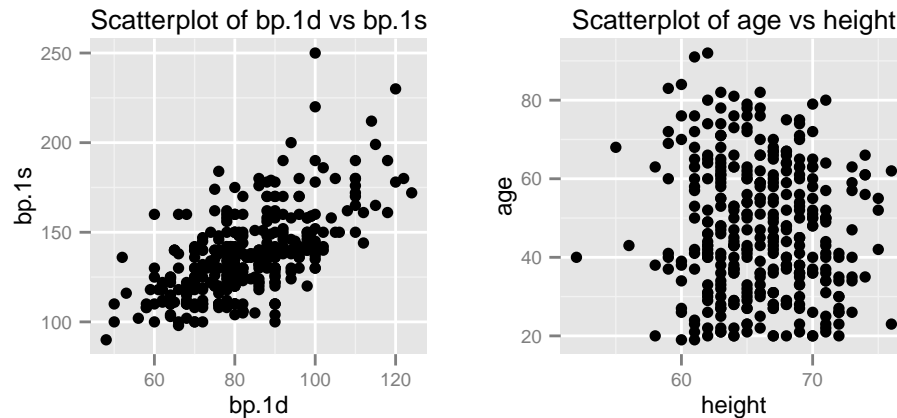
The mean, median and mode of `glyhb` are all approximately 5. The distribution of `glyhb` is left-skewed.

2.



The mean, median and mode of `chol` are all approximately 200. The distribution of `chol` is better approximated with a Gaussian distribution.

3.

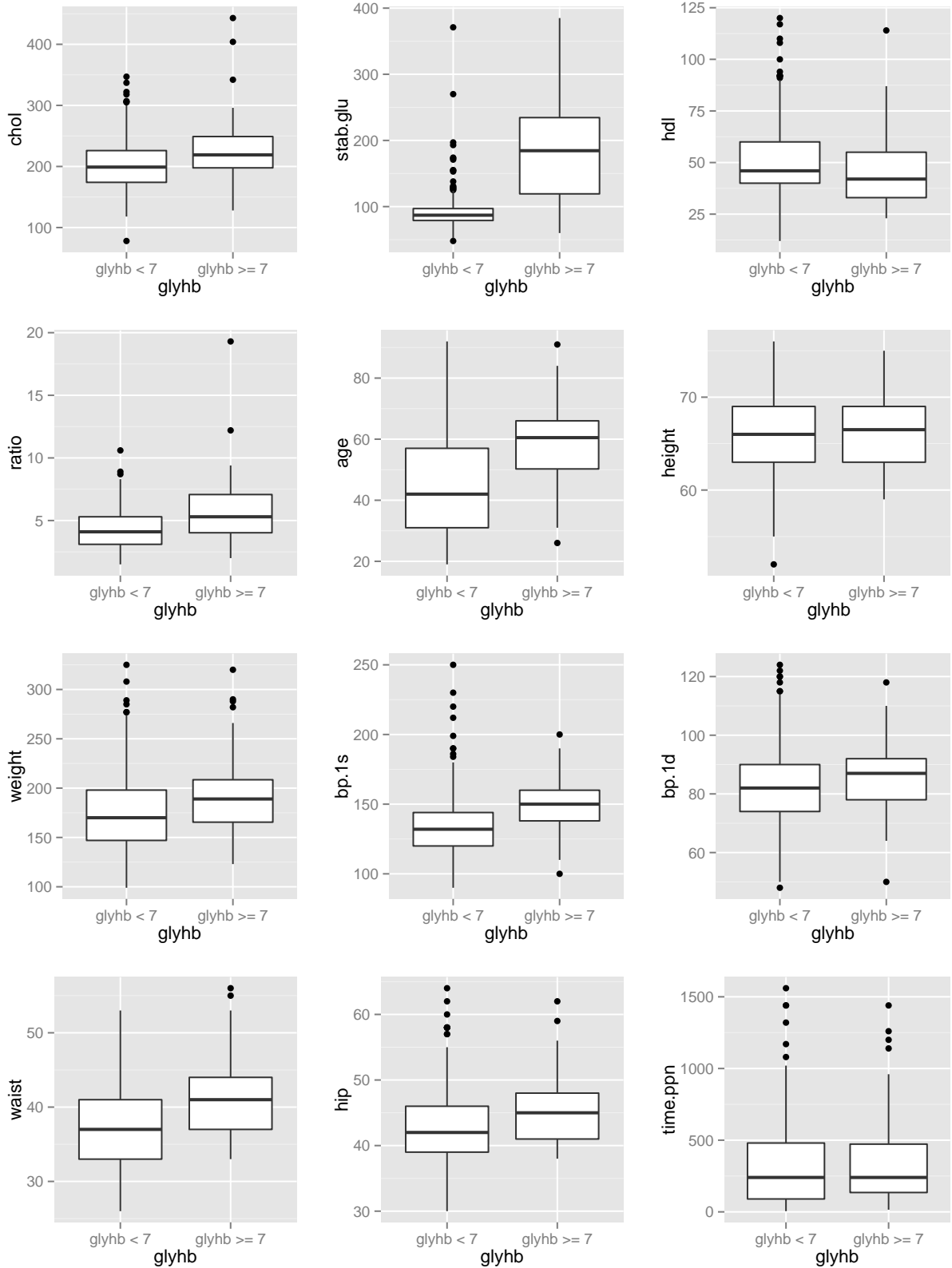


The scatterplot of `bp.1s` and `bp.1d` is near-linear, so they are approximately dependent. The scatterplot of `age` and `weight` is random, so they are approximately independent.

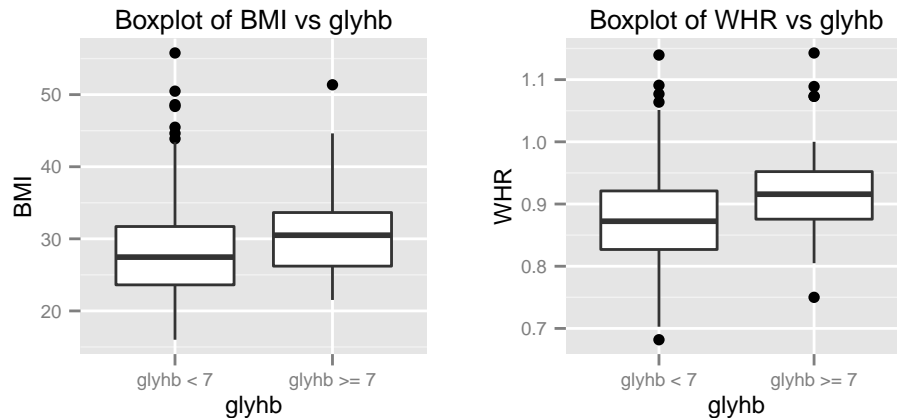
4.

- `chol`: The two distributions have small difference, so it may BE a relevant feature.
- `stab.glu`: The two distributions have substantial difference, so it may BE a relevant feature.
- `hdl`: The two distributions have small difference, so it may BE a relevant feature.
- `ratio`: The two distributions have small difference, so it may BE a relevant feature.
- `age`: The two distributions have substantial difference, so it may BE a relevant feature.
- `height`: The two distributions have little difference, so it may NOT BE a relevant feature.
- `weight`: The two distributions have small difference, so it may BE a relevant feature.
- `bp.1s`: The two distributions have small difference, so it may BE a relevant feature.
- `bp.1d`: The two distributions have small difference, so it may BE a relevant feature.
- `waist`: The two distributions have small difference, so it may BE a relevant feature.
- `hip`: The two distributions have small difference, so it may BE a relevant feature.
- `time.ppn`: The two distributions have small difference, so it may NOT BE a relevant feature.

Boxplots of each feature vs glyhb



5.



6. In light of these first experiments, `hdl`, `stab.glu`, `age`, `weight`, `bp.1s`, `bp.1d`, `waist` and `hip` seem related to the presence of type II diabetes; `chol`, `ratio`, `height` and `time.ppn` seem unrelated to the presence of type II diabetes.

### 3 Parametric Inference

1.

$$X \sim \text{Gamma}(\alpha, \beta) = \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x}$$

$$E(X) = \frac{\alpha}{\beta}$$

$$E(X^2) = \text{Var}(X) + [E(X)]^2$$

$$= \frac{\alpha}{\beta^2} + \left(\frac{\alpha}{\beta}\right)^2$$

$$= \frac{\alpha(\alpha + 1)}{\beta^2}$$

$$\begin{cases} E(X) = \frac{\alpha}{\beta} \\ E(X^2) = \frac{\alpha(\alpha+1)}{\beta^2} \end{cases} \Rightarrow \begin{cases} \alpha = \frac{[E(X)]^2}{\text{Var}(x)} \\ \beta = \frac{E(X)}{\text{Var}(x)} \end{cases} \Rightarrow \begin{cases} \hat{\alpha}_{MOM} = \frac{\bar{X}_n}{\frac{1}{n} \sum_{i=1}^n (X_i - \bar{X}_n)^2} \\ \hat{\beta}_{MOM} = \frac{\bar{X}_n^2}{\frac{1}{n} \sum_{i=1}^n (X_i - \bar{X}_n)^2} \end{cases}$$

```
gamma.bootstrap <- function(x) {
  alpha.mom <- mean(x)^2/var(x)
  beta.mom <- mean(x)/var(x)

  bootstrap <- sapply(1:1000, function(i) {
    samples <- sample(x, length(x), replace=TRUE)
    alpha.sample <- mean(samples)^2/var(samples)
    beta.sample <- mean(samples)/var(samples)
    return(c(alpha.sample, beta.sample))
  })

  CIs <- sapply(1:2, function(i) {
    CI <- quantile(bootstrap[i, ], probs=c(0.025, 0.975))
    return(CI)
  })
}
```

```

colnames(CIs) <- c("alpha", "beta")

return(CIs)
}

CI.BMI <- gamma.bootstrap(data.df$BMI)

#####
CI.BMI

##          alpha      beta
## 2.5%  15.77434 0.5420062
## 97.5% 21.52204 0.7547185

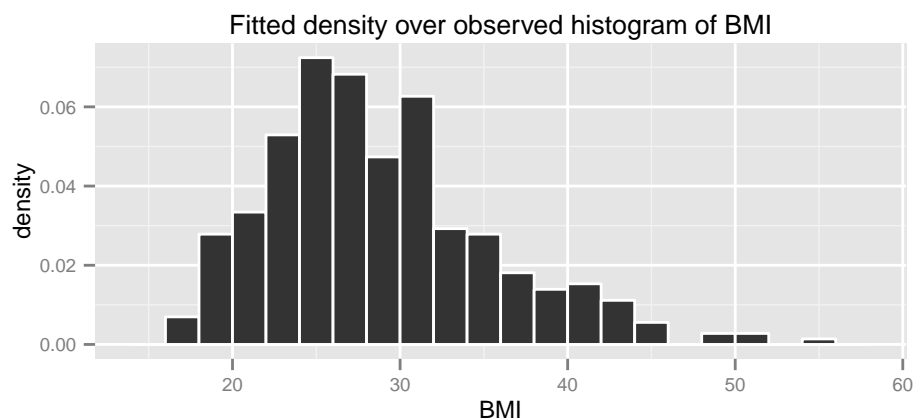
#####

```

```

ggplot(data.df) +
  geom_histogram(aes(x=BMI, y=..density..), binwidth=2, col="white") +
  stat_function(fun=function(x)
    dgamma(x, shape=alpha.mom, rate=beta.mom), col="white") +
  labs(title="Fitted density over observed histogram of BMI") +
  theme(text=element_text(size=8.5))

```



2.

$$\hat{\mu}_{MLE} = \bar{X}_n$$

$$\hat{\sigma}_{MLE}^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X}_n)^2$$

```

normal.bootstrap <- function(x) {
  mu.mle <- mean(x)
  sigma.mle <- sd(x)

  bootstrap <- sapply(1:1000, function(i) {
    samples <- sample(x, length(x), replace=TRUE)
    mu.sample <- mean(samples)
    sigma.sample <- sd(samples)
    return(c(mu.sample, sigma.sample))
  })
}

```

```

})

CIs <- sapply(1:2, function(i) {
  CI <- quantile(bootstrap[i, ], probs=c(0.025, 0.975))
  return(CI)
})
colnames(CIs) <- c("mu", "sigma")

return(CIs)
}

CI.WHR <- normal.bootstrap(data.df$WHR)

#####
CI.WHR

##           mu      sigma
## 2.5%  0.8742232 0.06755450
## 97.5% 0.8898956 0.08004401

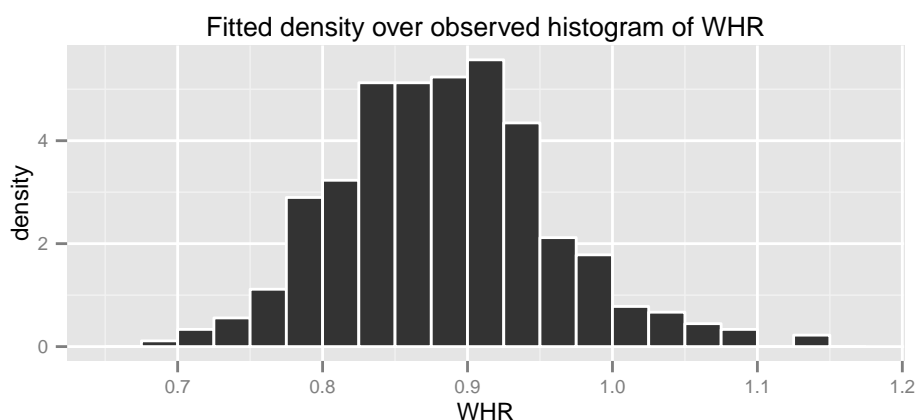
#####

```

```

ggplot(data.df) +
  geom_histogram(aes(x=WHR, y=..density..), binwidth=0.025, col="white") +
  stat_function(fun=function(x)
    dnorm(x, mean=mu.mle, sd=sigma.mle), col="white") +
  labs(title="Fitted density over observed histogram of WHR") +
  theme(text=element_text(size=8.5))

```



3. data.df\$gender.glyhb.cond <- NA  
 data.df[data.df\$gender=="male" & data.df\$glyhb>=7, ]\$gender.glyhb.cond <-  
 "male & (glyhb >= 7)"  
 data.df[data.df\$gender=="female" & data.df\$glyhb>=7, ]\$gender.glyhb.cond <-  
 "female & (glyhb >= 7)"  
 data.df[data.df\$gender=="male" & data.df\$glyhb<7, ]\$gender.glyhb.cond <-  
 "male & (glyhb < 7)"  
 data.df[data.df\$gender=="female" & data.df\$glyhb<7, ]\$gender.glyhb.cond <-

```

"female & (glyhb < 7)"

conditions <- c("male & (glyhb >= 7)", "female & (glyhb >= 7)",
               "male & (glyhb < 7)", "female & (glyhb < 7)")

gamma.bootstrap2 <- function(x) {
  alpha.mom <- mean(x)^2/var(x)
  beta.mom <- mean(x)/var(x)

  bootstrap <- sapply(1:1000, function(i) {
    samples <- sample(x, length(x), replace=TRUE)
    mu.sample <- mean(samples)
    sigma.sample <- sd(samples)
    return(c(mu.sample, sigma.sample))
  })

  CIs <- sapply(1:2, function(i) {
    CI <- quantile(bootstrap[i, ], probs=c(0.025, 0.975))
    return(CI)
  })
  colnames(CIs) <- c("mu", "sigma")

  return(CIs)
}

CIs.BMI <- lapply(conditions, function(x) {
  gender.glyhb.df <- subset(data.df, gender.glyhb.cond==x)
  CIs.BMI <- gamma.bootstrap2(gender.glyhb.df$BMI)
  return(CIs.BMI)
})
names(CIs.BMI) <- conditions

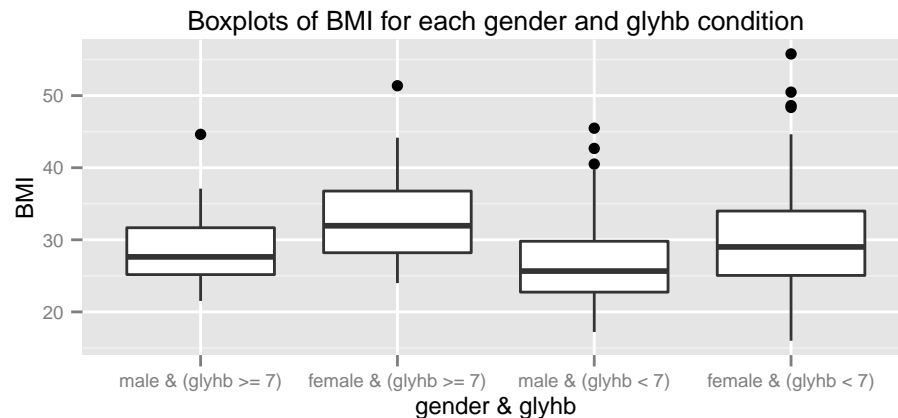
#####
CIs.BMI

## $`male & (glyhb >= 7)`
##           mu      sigma
## 2.5%  26.95963  3.418566
## 97.5% 30.80594  7.070036
##
## $`female & (glyhb >= 7)`
##           mu      sigma
## 2.5%  30.90487  4.660985
## 97.5% 35.69416  8.293779
##
## $`male & (glyhb < 7)`
##           mu      sigma
## 2.5%  25.48804  4.72097
## 97.5% 27.38754  6.40592
##
## $`female & (glyhb < 7)`
##           mu      sigma
## 2.5%  28.76716  6.216621
## 97.5% 30.76864  7.802709

```

```
#####
```

```
ggplot(data.df) +
  geom_boxplot(aes(x=factor(gender.glyhb.cond, levels=conditions), y=BMI)) +
  labs(title="Boxplots of BMI for each gender and glyhb condition",
        x="gender & glyhb") +
  theme(text=element_text(size=8.5))
```



```
CIs.WHR <- lapply(conditions, function(x) {
  gender.glyhb.df <- subset(data.df, gender.glyhb.cond==x)
  CIs.WHR <- normal.bootstrap(gender.glyhb.df$WHR)
  return(CIs.WHR)
})
names(CIs.WHR) <- conditions
```

```
#####
```

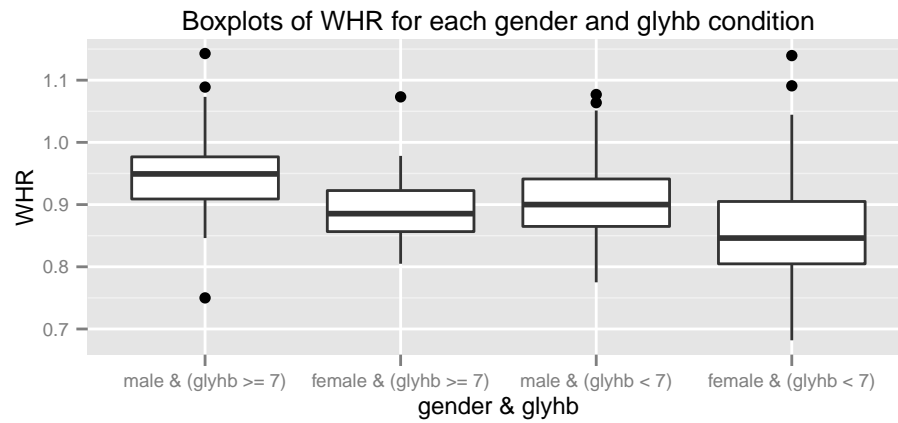
```
CIs.WHR
```

```
## $`male & (glyhb >= 7)`
##           mu      sigma
## 2.5%  0.9170921 0.04852926
## 97.5% 0.9807403 0.10435834
##
## $`female & (glyhb >= 7)`
##           mu      sigma
## 2.5%  0.8745839 0.04175829
## 97.5% 0.9151449 0.07790498
##
## $`male & (glyhb < 7)`
##           mu      sigma
## 2.5%  0.8945964 0.05586194
## 97.5% 0.9163876 0.07088215
##
## $`female & (glyhb < 7)`
##           mu      sigma
## 2.5%  0.8445274 0.06136025
## 97.5% 0.8646460 0.07883802
```

```
#####
```



```
ggplot(data.df) +
  geom_boxplot(aes(x=factor(gender.glyhb.cond, levels=conditions), y=WHR)) +
  labs(title="Boxplots of WHR for each gender and glyhb condition",
        x="gender & glyhb") +
  theme(text=element_text(size=8.5))
```



## 4 Testing

- 1.
- 2.
- 3.
- 4.
- 5.
- 6.

## 5 Regression

- 1.
- 2.
- 3.
- 4.
- 5.
- 6.
- 7.