# Homework\_2

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#### Problem 1

```
a.)
# parameters for x1
x1_alpha <- 1
x1_beta <- 5
x1_mu \leftarrow x1_alpha*x1_beta
x1_sig <- sqrt(x1_alpha*x1_beta^2)</pre>
x1_var <- x1_alpha*x1_beta^2</pre>
x1_skew <- 2/sqrt(x1_alpha)</pre>
x1_params <- c(alpha = x1_alpha</pre>
                 , beta = x1_beta
                 , mu = x1_mu
                 , sig = x1_sig
                 , var = x1_var
                 , skew = x1_skew)
# parameters for x2
x2alpha <- 5
x2_beta <- 1
x2_mu \leftarrow x2_alpha*x2_beta
x2_sig <- sqrt(x2_alpha*x2_beta^2)</pre>
x2_var <- x2_alpha*x2_beta^2</pre>
x2_skew <- 2/sqrt(x2_alpha)</pre>
x2_{params} \leftarrow c(alpha = x2_{alpha})
                 , beta = x2_beta
                 , mu = x2_mu
                 , sig = x2\_sig
                 , var = x2_var
                 , skew = x2\_skew)
# create param df
param_df <- as.data.frame(rbind(x1_params,x2_params))</pre>
# print values
knitr::kable(param_df)
```

	alpha	beta	mu	sig	var	skew
x1_params	1	5	5	5.000000	25	2.0000000
$x2$ _params	5	1	5	2.236068	5	0.8944272

```
# set range for distributions
x1_range \leftarrow seq(0, x1_mu + 3*x1_sig, 0.01)
x2_range <- seq(0, x2_mu + 3*x2_sig,0.01)</pre>
# draw from distributions
x_1 <- dgamma(x1_range, x1_alpha, rate =1/x1_beta)</pre>
x_2 <- dgamma(x2_range, x2_alpha, rate =1/x2_beta)</pre>
# get 2 plots on same output window
par(mfrow=c(1,2))
# fix error for margin sizes
par(mar=c(1,1,1,1))
plot(x1_range, x_1, type='l', ylim=c(0, max(x_1)+0.01))
plot(x2_range, x_2, type='l', ylim=c(0, max(x_2)+0.01))
                                              0.20
                                              0.15
                                              0.10
                                              0.00
b.)
# parameters for x1
x1_alpha <- 2
x1_beta <- 4
x1_mu \leftarrow x1_alpha*x1_beta
x1_sig <- sqrt(x1_alpha*x1_beta^2)</pre>
x1_var <- x1_alpha*x1_beta^2</pre>
x1_skew <- 2/sqrt(x1_alpha)</pre>
x1_params <- c(alpha = x1_alpha</pre>
                 , beta = x1_beta
                , mu = x1_mu
```

```
, sig = x1_sig
                 , var = x1_var
                 , skew = x1_skew)
# parameters for x2
x2alpha <- 8
x2_beta <- 2
x2_mu <- x2_alpha*x2_beta</pre>
x2_sig <- sqrt(x2_alpha*x2_beta^2)</pre>
x2_var <- x2_alpha*x2_beta^2</pre>
x2_skew <- 2/sqrt(x2_alpha)</pre>
x2_{params} \leftarrow c(alpha = x2_{alpha})
                 , beta = x2_beta
                 , mu = x2_mu
                 , sig = x2\_sig
                 , var = x2_var
                 , skew = x2\_skew)
# create param df
param_df <- as.data.frame(rbind(x1_params,x2_params))</pre>
# print values
knitr::kable(param_df)
```

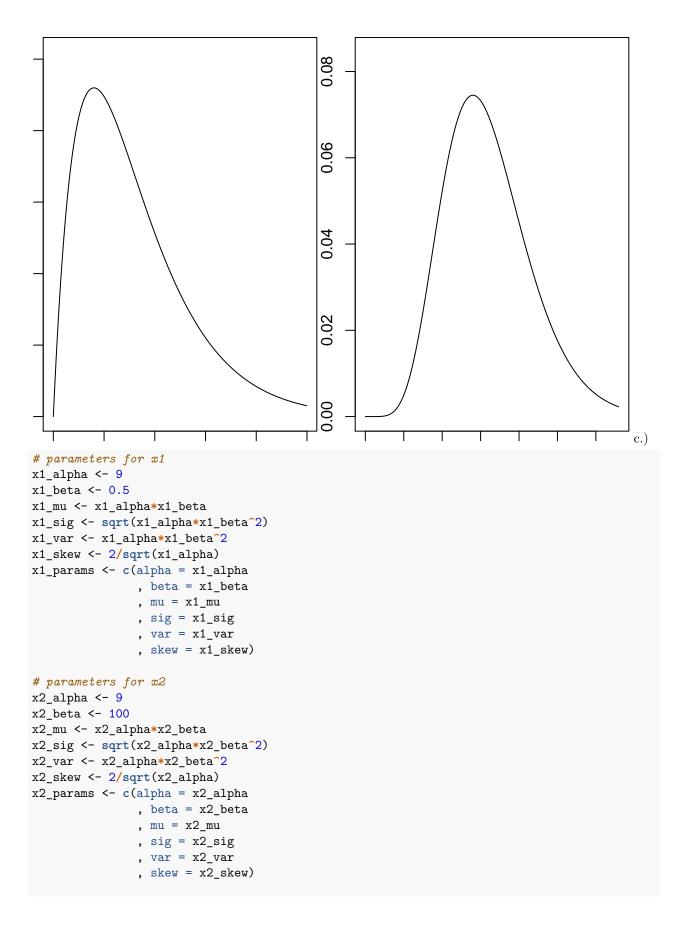
	alpha	beta	mu	sig	var	skew
x1_params	2	4	8	5.656854	32	1.4142136
$x2$ _params	8	2	16	5.656854	32	0.7071068

```
# set range for distributions
x1_range <- seq(0, x1_mu + 3*x1_sig,0.01)
x2_range <- seq(0, x2_mu + 3*x2_sig,0.01)

# draw from distributions
x_1 <- dgamma(x1_range, x1_alpha, rate =1/x1_beta)
x_2 <- dgamma(x2_range, x2_alpha, rate =1/x2_beta)

# get 2 plots on same output window
par(mfrow=c(1,2))

# fix error for margin sizes
par(mar=c(1,1,1,1))
plot(x1_range, x_1, type='l', ylim=c(0,max(x_1)+0.01))
plot(x2_range, x_2, type='l', ylim=c(0,max(x_2)+0.01))</pre>
```



```
# create param df
param_df <- as.data.frame(rbind(x1_params,x2_params))

# print values
knitr::kable(param_df)</pre>
```

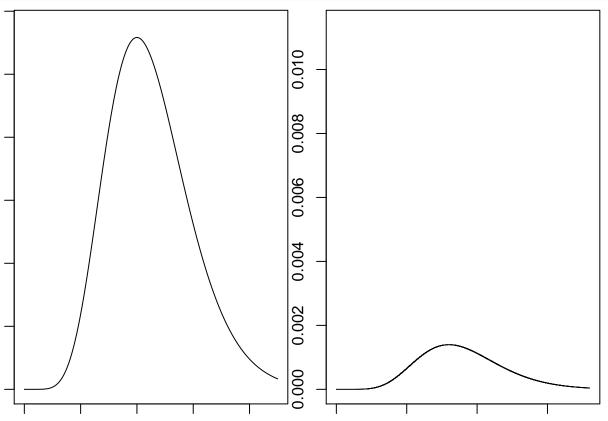
	alpha	beta	mu	sig	var	skew
x1_params	9	0.5	4.5	1.5	2.25	0.6666667
$x2$ _params	9	100.0	900.0	300.0	90000.00	0.6666667

```
# set range for distributions
x1_range <- seq(0, x1_mu + 3*x1_sig,0.01)
x2_range <- seq(0, x2_mu + 3*x2_sig,0.01)

# draw from distributions
x_1 <- dgamma(x1_range, x1_alpha, rate =1/x1_beta)
x_2 <- dgamma(x2_range, x2_alpha, rate =1/x2_beta)

# get 2 plots on same output window
par(mfrow=c(1,2))

# fix error for margin sizes
par(mar=c(1,1,1,1))
plot(x1_range, x_1, type='1', ylim=c(0,max(x_1)+0.01))
plot(x2_range, x_2, type='1', ylim=c(0,max(x_2)+0.01))</pre>
```



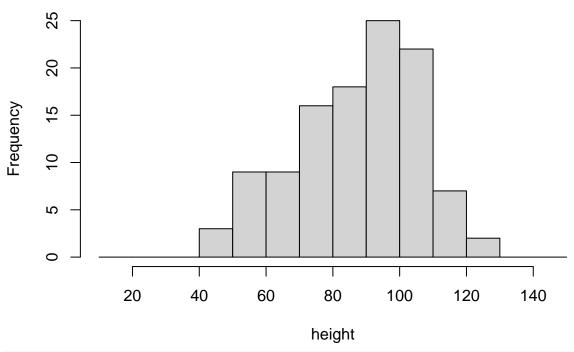
- d.) Not possible. Different skew implies different alphas. Which implies you can get the same mean, but variance will never equal
- e.) Not possible. To have the same skew and mean, you need to fix both alpha and beta. Which implies variance will be the same as well
- f.) Not possible. You would need to fix both alpha and beta to achieve the same variance and different skew. But this implies mean is the same as well.

## Problem 2

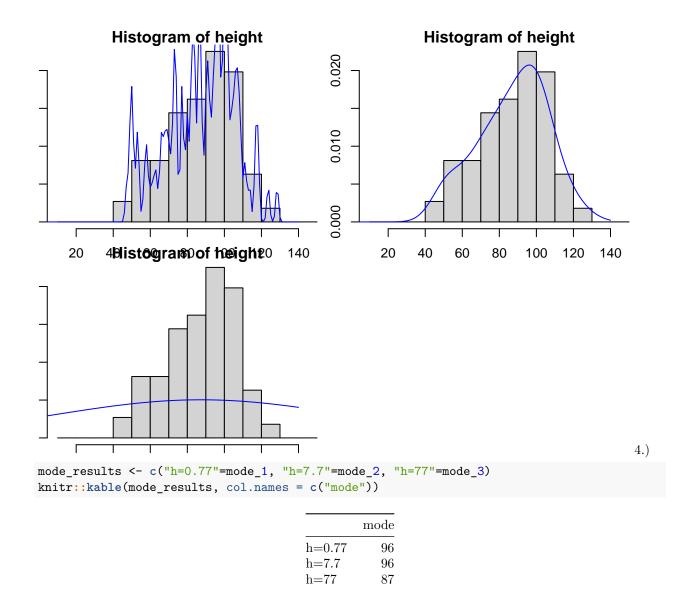
```
# load data
treedat <- read.csv2("/cloud/project/treedat.csv", sep=",")

# look at data
height <- as.vector(as.numeric(treedat$height))
hist(x=height, breaks=10*seq(1:15))</pre>
```

# Histogram of height



```
value_2 <- mean(norm_density((x-height)/h)/h)</pre>
                     return(value_2)
                   }
# apply this for all x
kde_2 = function(x) {
                       sapply(x,kde)
# set up plot
par(mar=c(1,1,1,1))
par(mfrow=c(2,2))
grid <- seq(1,140,by=1)
# set bandwidth and plot kde on histogram
h = 0.77
hist(x=height, freq=FALSE, breaks=10*seq(1:15))
lines(grid, kde_2(grid), col="blue")
# find mode
mode_1 <- which(kde_2(grid)==max(kde_2(grid)))</pre>
prob_1 <- sum(kde_2(grid)[1:91])</pre>
h = 7.7
hist(x=height, freq=FALSE, breaks=10*seq(1:15))
lines(grid, kde_2(grid), col="blue")
mode_2 <- which(kde_2(grid)==max(kde_2(grid)))</pre>
prob_2 <- sum(kde_2(grid)[1:91])</pre>
hist(x=height, freq=FALSE, breaks=10*seq(1:15))
lines(grid, kde_2(grid), col="blue")
mode_3 <- which(kde_2(grid)==max(kde_2(grid)))</pre>
prob_3 <- sum(kde_2(grid)[1:91])</pre>
```



The change in bandwidth does not seem to heavily influence the mode. Which makes sense because the difference in values isnt changing so the h is just putting it on a different scale.

A practitioner could start with the rule of thumb 7.7 and adjust from there through trial and error depending what looks the best against the data.

A bad choice for bandwidth could result in very bad estimates for all values of x and affect your whatever analyses you may be doing after estimation.

5.)

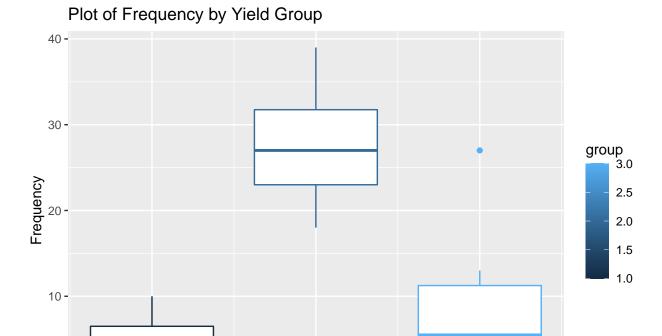
```
prob_results <- c("h=0.77"=prob_1, "h=7.7"=prob_2, "h=77"=prob_3)
knitr::kable(prob_results, col.names = c("P(X<92)"))</pre>
```

	P(X<92)
h=0.77	0.5297984
h=7.7	0.5438774
h=77	0.3845063

Sum the values of the kde where X<92. This would give you the area under the curve. The probablity seems to drop relatively sharply as h went from 7.7 to 77. (-16%) From that drop, I would say yes probablity depends on the bandwidth.

#### Problem 3

```
a.)
# create dataframe
soybean_df \leftarrow data.frame(yield=c(seq(14,48,2)), freq=c(1,4,1,5,7,10,26,22,39,33,28,18,27,13,4,5,6,1))
# tidyverse solution to find mode
sb_mode = soybean_df %>%
 filter(freq==max(freq)) %>%
  select(yield)
# calculate mean
sb_x_bar = with(soybean_df, sum(freq*yield)/sum(freq))
# list all elements out in vector, not just by frequencies
expanded_soybean_vector <- rep(soybean_df$yield, soybean_df$freq)</pre>
# find median
sb_median <- median(expanded_soybean_vector)</pre>
# dataframe of results
results_df <- data.frame(mean = sb_x_bar, median=sb_median, mode=sb_mode[1,1])
# calculate sample standard deviation
sb_s_bar <- with(soybean_df, sqrt(sum(freq*(yield-sb_x_bar)^2)/(sum(freq)-1)))
# calculate sample variance
sb_variance <- sb_s_bar^2</pre>
# calculate coefficient of variation
sb_s_bar/sb_x_bar
## [1] 0.1968789
# aroup data
grouped_soybean_df <- cbind(soybean_df, group=c(rep(1,6), rep(2,6), rep(3,6)))</pre>
# create boxplot
ggplot(grouped_soybean_df, aes(x=group, y=freq, group=group, col=group)) +
  geom boxplot() +
  ggtitle("Plot of Frequency by Yield Group") +
 xlab("Yield Group") +
 ylab("Frequency")
```



The data were split into three equal yield groups (n=6). Group1=Yields 14-24, Group2=Yields 26-36, and Group3 Yields 38-48. Yield sizes in the middle group  $(group\ 2)$  appear to be far more frequent than the other groups

3

Yield Group

0 -

# Problem 4

a.)

Sample mean for X:

$$X = a + Y$$
We know,  $\bar{Y} = \frac{1}{n} \sum_{i=1}^{n} Y_i$ 

$$\implies \bar{X} = \frac{1}{n} \sum_{i=1}^{n} a + Y_i$$

$$= \frac{1}{n} (\sum_{i=1}^{n} (Y_i) + na)$$

$$= \frac{1}{n} \sum_{i=1}^{n} (Y_i) + a$$

$$= \bar{Y} + a \blacksquare$$

Sample mean for U:

$$U = b * Z$$
Similarly,  $\bar{Z} = \frac{1}{n} \sum_{i=1}^{n} Z_i$ 

$$\implies \bar{U} = \frac{1}{n} \sum_{i=1}^{n} b Z_i$$

$$= b \frac{1}{n} \sum_{i=1}^{n} Z_i$$

$$= b \bar{Z} \blacksquare$$

b.)

Sample variance for X:

$$\begin{split} X &= a + Y \\ \text{We know, } s_Y^2 &= \frac{\sum (y_i - \bar{y})^2}{n-1} \\ \implies s_X^2 &= \frac{\sum ((a+y_i) - (\bar{Y}+a))^2}{n-1} \text{ , distribute the negative} \\ &= \frac{\sum (a+y_i - \bar{Y}-a)^2}{n-1} \text{ , a's cancel} \\ &= \frac{\sum (y_i - \bar{Y})^2}{n-1} \blacksquare \end{split}$$

Sample standard deviation for X:

$$\sqrt{s_X^2} = s_X = \sqrt{\frac{\sum (y_i - \bar{Y})^2}{n-1}} \ \blacksquare$$

Sample variance for U:

$$U = b * Z$$
We know,  $s_Z^2 = \frac{\sum (z_i - \bar{z})^2}{n - 1}$ 

$$\implies s_U^2 = \frac{\sum ((bz_i) - (b\bar{z}))^2}{n - 1}$$

$$= \frac{\sum (b^2 z_i^2 - 2b^2 z_i \bar{z} + b^2 \bar{z}^2)}{n - 1}$$

$$= \frac{b^2 \sum (z_i^2 - 2z_i \bar{z} + \bar{z}^2)}{n - 1}$$

$$= \frac{b^2 \sum (z_i - \bar{z})^2}{n - 1} \blacksquare$$

Sample standard deviation for U:

$$\sqrt{s_U^2} = s_U = \sqrt{\frac{b^2 \sum (z_i - \bar{Z})^2}{n-1}} \blacksquare$$

c.)

The median's position remains unchanged for both X and U

Denote median as  ${\cal M}$ 

If n is odd, 
$$M = \frac{n+1}{2}th$$
 observation

If n is even, 
$$M = \frac{\frac{n+1}{2}th\ obs + \frac{n}{2}th\ obs}{2}$$

## Problem 5

1.) Prove: 
$$E(\bar{X}) = \mu$$
 
$$E(\bar{X}) = E(\frac{1}{n} \sum_{i=1}^{n} x_i) \text{, pull the constant out}$$
 
$$= \frac{1}{n} E(\sum_{i=1}^{n} x_i) \text{, by linearity we can move E()}$$
 
$$= \frac{1}{n} \sum_{i=1}^{n} E(x_i)$$
 
$$= \frac{1}{n} \sum_{i=1}^{n} \mu$$
 
$$= \frac{1}{n} n \mu$$
 
$$= \mu \blacksquare$$

Prove:  $E(S^2) = \hat{\sigma}^2$ 

2.)

$$E(S^2) = E(\frac{\sum (x_i - \bar{x})^2}{n - 1})$$

$$= \frac{1}{n - 1}E(\sum (x_i - \bar{x})^2) \text{, expanding we get}$$

$$= \frac{1}{n - 1}E(\sum x_i^2 - 2x_i\bar{x} + \bar{x}^2) \text{, distribute sigma}$$

$$= \frac{1}{n - 1}E(\sum x_i^2 - \sum 2x_i\bar{x} + \sum \bar{x}^2)$$

$$= \frac{1}{n - 1}E(\sum x_i^2 - 2\bar{x}\sum x_i + n\bar{x}^2) \text{, solving for } \sum x_i$$

$$= \frac{1}{n - 1}E(\sum x_i^2 - 2\bar{x} * n\bar{x} + n\bar{x}^2)$$

$$= \frac{1}{n - 1}E(\sum x_i^2 - n\bar{x}^2) \text{, using linearity}$$

$$= \frac{1}{n - 1}\sum E(x_i^2) - E(n\bar{x}^2) \text{, subbing in for known identites we get}$$

$$= \frac{1}{n - 1}\sum (\sigma^2 + \mu^2) - n(\frac{\sigma^2}{n} + \mu^2) \text{, evaluating sigma for the left term}$$

$$= \frac{1}{n - 1}(n\sigma^2 + n\mu^2 - \sigma^2 - n\mu^2)$$

$$= \frac{1}{n - 1}(n\sigma^2 - \sigma^2)$$

$$= \frac{1}{n - 1}(n - 1)\sigma^2$$

$$= \sigma^2 \blacksquare$$