Berkstats Day 1: First Steps in R

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The R-Console

```
print("Hello world")
## [1] "Hello world"
```

Variables and Vectors

```
a <- c(10,22,33, 22, 40)
names(a) <- c("Andy", "Betty", "Claire", "Daniel", "Eva")
a
## Andy Betty Claire Daniel Eva
## 10 22 33 22 40
a[3]
## Claire
## 33
a["Claire"]
## Claire
## 33</pre>
```

Compute the Mean

```
# own implementation: use R-function for summing up the elements in a vector
# and getting the number of elements in a vector
sum(a) / length(a)

## [1] 25.4
# or use the function delivered with the R installation
mean(a)
## [1] 25.4
```

Compute the Median

```
# own implementation
# 1) sort the vector in ascending order (if not yet ordered)
sorted_a <- sort(a)</pre>
```

```
# 2) get the index of the element in the middle (i.e., the [(N+1)/2]th element)
middle <- (length(sorted_a)+1)/2
\# 3) check whether the index of the element we get is a fraction
is_fraction <- (middle %% 1) != 0</pre>
# 4) if so, take the mean of the element above and below as median
     else, take that middle element as median
if (is_fraction) {
     (sorted_a[floor(middle)] + sorted_a[ceiling(middle)]) / 2
} else {
     sorted_a[middle]
## Daniel
##
       22
# function delivered with R-installation
median(a)
## [1] 22
```

Compute the Mode

```
# count occurrences
counts <- table(a)
# which value occurs most often
which.max(counts)

## 22
## 2
# write your own mode-function:
mymode <- function(x) {
    counts <- table(x)
    x_mode <- as.numeric(names(which.max(counts)))

    return(x_mode)
}

# apply your own mode-function:
mymode(a)

## [1] 22</pre>
```

Measures of Variability

```
range(a)

## [1] 10 40

var(a)

## [1] 132.8
```

```
sd(a)
## [1] 11.52389
```

Compute the Standard Deviation

```
# own implementaion
sqrt(sum((a-mean(a))^2) / (length(a) - 1))
## [1] 11.52389
# function delivered with R-installation
sd(a)
## [1] 11.52389
```

Random Draws and Distributions

```
normal_distr <- rnorm(1000)
hist(normal_distr)</pre>
```

Histogram of normal_distr

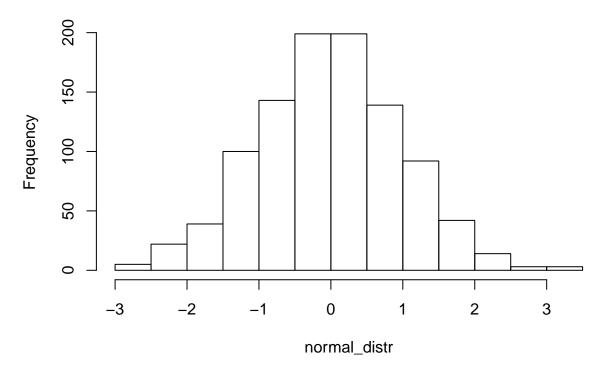
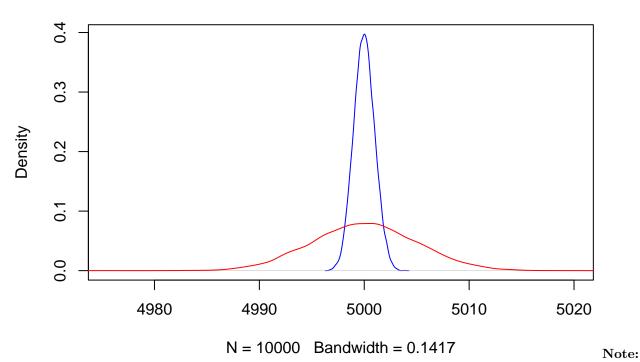


Illustration of Variability

Income Distribution



the red curve illustrates the distribution of the sample with a large standard deviation (a lot of variability) whereas the blue curve illustrates the one with a rather small standard deviation.

Skewness and Kurtosis

```
# Install the R-package called "moments" with the following command (if not installed yet):
# install.packages("moments")
# load the package
library(moments)
```

Recall Day 1's slides on Skewness and Kurtosis. A helpful way to memorize what a certain value of either of these two statistics means is to visualize the respective distribution (as shown in the slides).

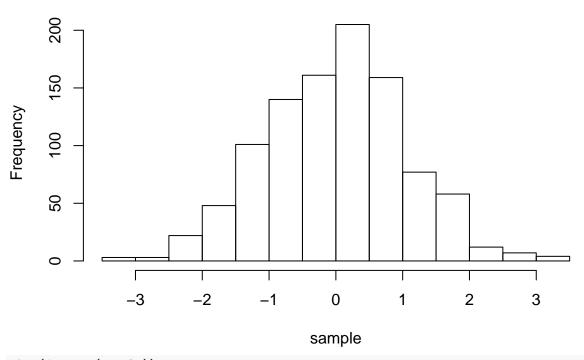
Skewness

Skewness refers to how symetric the frequency distribution of a variable is. For example, a distribution can be 'positively skewed' meaning it has a long tail on the right and a lot of 'mass' (observations) on the left. We can see that when visualizing the distribution in a histogram or a density plot. Lets have a look at this in R (note the comments in the code explaing what each line does):

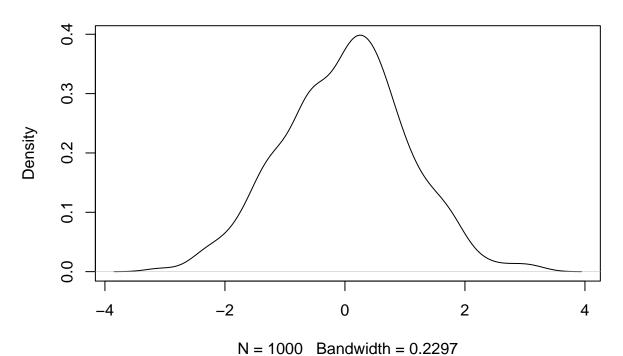
```
# draw a random sample of simulated data from a normal distribution
# the sample is of size 1000 (hence, n = 1000)
sample <- rnorm(n = 1000)

# plot a histogram and a density plot of that sample
# note that the distribution is neither strongly positively nor negatively skewed
# (this is to be expected, as we have drawn a sample from a normal distribution!)
hist(sample)</pre>
```

Histogram of sample



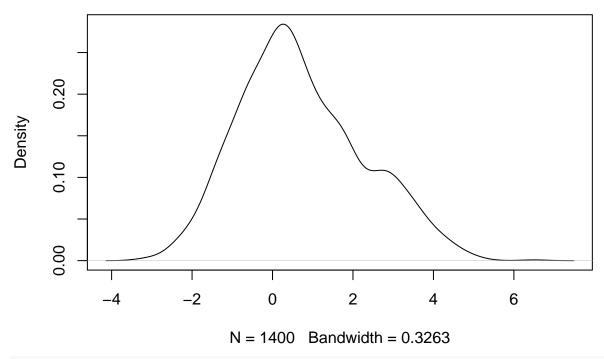
plot(density(sample))



now compute the skewness
skewness(sample)

[1] 0.005174825

Now we intentionally change our sample to be strongly positively skewed
We do that by adding some outliers (observations with very high values) to the sample
sample <- c(sample, (rnorm(200) + 2), (rnorm(200) + 3))
Have a look at the distribution and re-calculate the skewness
plot(density(sample))</pre>



skewness(sample)

[1] 0.4038113

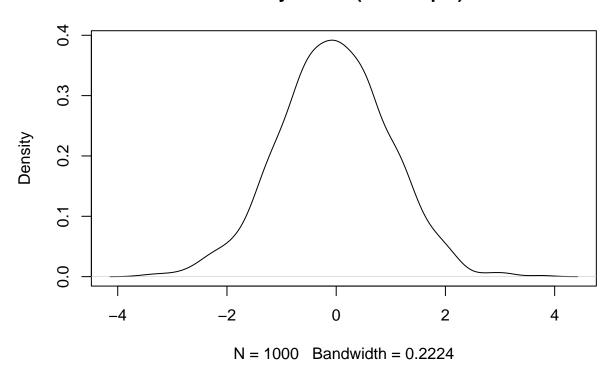
#

Kurtosis

Kurtosis refers to how much 'mass' a distribution has in its 'tails'. It thus tells us something about whether a distribution tends to have a lot of outliers. Again, plotting the data can help us understand this concept of kurtosis. Lets have a look at this in R (note the comments in the code explaing what each line does):

```
# draw a random sample of simulated data from a normal distribution
# the sample is of size 1000 (hence, n = 1000)
sample <- rnorm(n = 1000)

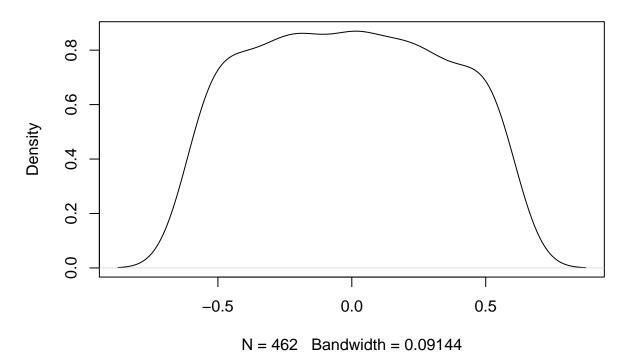
# plot the density & compute the kurtosis
plot(density(sample))</pre>
```



kurtosis(sample)

[1] 3.233971

```
### [1] 3.233311
# now lets remove observations from the extremes in this distribution
# we thus intentionally alter the distribution to have less mass in its tails
sample <- sample[ sample > -0.6 & sample < 0.6]
# plot the distribution again and see how the tails of it (and thus the kurtosis has changed)
plot(density(sample))</pre>
```



```
# re-calculate the kurtosis
kurtosis(sample)
```

[1] 1.843965

as expected, the kurtosis has now a lower value

Implement the formulas for skewness and kurtosis in R

Skewness

```
# own implementation
sum((sample-mean(sample))^3) / ((length(sample)-1) * sd(sample)^3)

## [1] 0.02736003

# implementation in moments package
skewness(sample)

## [1] 0.02738969

Kurtosis

# own implementation
sum((sample-mean(sample))^4) / ((length(sample)-1) * sd(sample)^4)

## [1] 1.839974

# implementation in moments package
```

[1] 1.843965

kurtosis(sample)