AUA CS 108, Statistics, Fall 2019 Lecture 07

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Numerical Summaries

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► Summaries (Statistics) about the Center, Mean, Location

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- Summaries (Statistics) about the Spread, Variability

Statistical Measures for the Central Tendency/Location

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Here we want to answer to trhe questions: what are the typical values of our Dataset, where is our Data located at?

Assume we are given a 1D numerical Dataset $x: x_1, x_2, ..., x_n$.

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$$\bar{x} = mean(x) = \frac{x_1 + x_2 + \dots + x_n}{n}$$

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Drawback: Sensitive to outliers (non-typical elements)

Note: Sometimes this property is a plus, not a drawback! Say, if we want to have an estimator which is sensitive to outliers.

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Example: Consider the following Dataset:

1, 2, 3, 4, 5, 6, 789

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Example: Consider the following Dataset:

The mean of this is

```
mean(c(1,2,3,4,5,6,789))
```

```
## [1] 115.7143
```

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Example: Consider the following Dataset:

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Can we say here that the elements of our Dataset are 115.7143 plyus-minus something? Not exactly.

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Example: Consider the following Dataset:

The mean of this is

```
## [1] 115.7143
```

Can we say here that the elements of our Dataset are 115.7143 plyus-minus something? Not exactly.

Well, 115.7143 is not the typical value/center of our Dataset. This number gives us a wrong information about the elements of the Dataset.

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▶ The Trimmed (Truncated) Sample Mean: First we take a real number $r \in (0,0.5)$ (or, in percents, from 0 to 50%). We will drop the *lowest r percent and largest r percent* of our data, and then we will calculate the Sample Mean of the rest.

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So we take r (ratio, fraction to be deleted), we calculate $p = [r \cdot n]$. Then we sort our x in the acsending order, delete first p and last p values from this sorted array, and calculate the mean of the remaining Dataset.

Mathematically,

trimmed sample mean(
$$x$$
) = $\bar{x}_{trimmed}$ =

$$=\frac{x_{(p+1)}+x_{(p+2)}+\ldots+x_{(n-p-1)}+x_{(n-p)}}{n-2p}=\frac{\sum\limits_{k=p+1}^{n-p}x_{(k)}}{n-2p}.$$

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Example: See, for example, Scoring the Dive Competition.

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Idea of Trimming: Reduce the influence of outliers. This *Statistics* for the Central Tendency, Center, is more *robust* to outliers, extremes, than the ordinary mean.

```
x <- c(1, 10, 20, 30, 4, 50)
mean(x)

## [1] 19.16667
mean(x, trim = 0.4)

## [1] 15</pre>
```

Winsorized Sample Mean

▶ Winsorized Sample Mean: Again, to reduce the influence of outliers, one can calculate the Winsorized Sample Mean. Here we again take $r \in (0, 0.5)$, take $p = [n \cdot r]$, and calculate

winsorized sample mean(
$$x$$
) =

$$\frac{x_{(p+1)} + \dots + x_{(p+1)} + x_{(p+2)} + x_{(p+3)} + \dots + x_{(n-p-2)} + x_{(n-p-1)} + \dots + x_{(n-p-1)}}{n}$$

$$(p+1) \cdot x_{(p+1)} + \sum_{k=p+2}^{n-p-2} x_{(k)} + (p+1) \cdot x_{(n-p-1)}$$

n

Weighted Sample Mean

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weighted sample mean(x; w) =
$$\bar{x}_w = \frac{\sum_{k=1}^n w_k x_k}{\sum_{k=1}^n w_k}$$
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weighted sample mean
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.

The weight of data x_k is then $\frac{w_k}{\sum_{i=1}^n w_i}$.

```
x \leftarrow c(-1,2,3,2,3,1,4,5,10)

w \leftarrow c(0,1.2,1,1,5,3,2,3,1)

weighted.mean(x, w)
```

[1] 3.395349

sum(x*w)/sum(w)

[1] 3.395349

```
x <- c(-1,2,3,2,3,1,4,5, 10)
w <- c(0,1.2,1,1,5,3,2,3, 1)
weighted.mean(x, w)

## [1] 3.395349

We can check:</pre>
```

▶ The Sample Median: Sample Median is, in some sense, the central value, the middle value, of our Dataset, when sorted in the increasing order.

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The rigorous definition is: let $x : x_1, x_2, ..., x_n$ be our dataset.

▶ If *n* is **odd**, then we define

$$median(x) = x_{\left(\frac{n+1}{2}\right)};$$

▶ If *n* is **even**,

$$median(x) = \frac{1}{2} \cdot \left(x_{\left(\frac{n}{2}\right)} + x_{\left(\frac{n}{2}+1\right)}\right).$$

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Example: For

$$x:-1,2,3,1,2,4,9,$$

the Median is: OTB

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▶ If *n* is even: then, in the sorted list, we have 2 elements at the center. We take the average of these two elements.

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$$x: -1, 2, 3, 1,$$

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Calculation of the Median is simple in ${\bf R}$: just use the median function.

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```
x <- c(1,3,2, 4,2,3,2,2,1)
mean(x)
```

```
## [1] 2.222222
```

```
median(x)
```

```
## [1] 2
```

Calculation of the Median is simple in ${\bf R}$: just use the median function.

```
x \leftarrow c(1,3,2,4,2,3,2,2,1)
mean(x)
## [1] 2.22222
median(x)
## [1] 2
Now, let's add an outlier:
x < -c(x, 1000)
mean(x)
```

[1] 102 median(x)

[1] O

Important Property of the Median

► Half of the Datapoints are to the left of the Median, and half of the Datapoints are to the right

Example: Give OTB

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Example: The Sample Mode of the following Dataset:

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Remark: Mode can be non-unique. One can have several Modes in the Dataset.

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Remark: Mode can be calculated even for the Nominal Scale Categorical Datasets

Mode Calculation in R

We do not have a simple command in basic ${\bf R}$ to calculate all Modes in ${\bf R}$. Suggesion: write it by yourself!

Other Measures of the Central Tendency

Midrange,

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Other Measures of the Central Tendency

In Stat, one also considers the following Measures of the Central Tendency:

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Hodges–Lehmann statistic,

$$HLS(x) = median(mean(x_i, x_j) : j = 1, ..., n, i = 1, ..., j).$$

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Hodges–Lehmann statistic,

$$\mathit{HLS}(x) = \mathit{median} \big(\mathit{mean}(x_i, x_j) : j = 1, ..., n, i = 1, ..., j \big).$$

See others at Wiki

Statistical Measures for the Spread/Variability

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Here we want to answer to the questions: how spread/concentrated are our Datapoints, how much is the variability of our Data?

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 $x: x_1, x_2, ..., x_n.$

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$$X : X_1, X_2, ..., X_n.$$

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$$x_k - \bar{x} = x_k - mean(x),$$
 $k = 1, ..., n$

are called **Deviations of** x **from the Mean**.

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Similarly, **Deviations of** x **from the Median** are defined as the differences

$$x_k - median(x), \qquad k = 1, ..., n$$

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Similarly, **Deviations of** x **from the Median** are defined as the differences

$$x_k - median(x), \qquad k = 1, ..., n$$

Consider the Dataset islands from R:

```
head(islands, 3)
```

```
## Africa Antarctica Asia
## 11506 5500 16988
```

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head(islands, 3)

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To calculate Deviations from the Mean for this Dataset, we just use
x.bar <- mean(islands)
deviations <- islands - x.bar
head(deviations)</pre>
```

##	Africa	Antarctica	Asia	Australia Axel
##	10253.271	4247.271	15735.271	1715.271

Range

The simplest measure of the Spread is the Range:

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.

In **R**, the command range gives the pair $(x_{(1)}, x_{(n)})$, not their difference.

Say,

range(islands)

[1] 12 16988

Example, R code to Calculate the Range

We can define our custom function to calculate the Range as the difference:

```
my.range <- function(x){
  return(max(x)-min(x))
}</pre>
```

Example, R code to Calculate the Range

We can define our custom function to calculate the Range as the difference:

```
my.range <- function(x){
   return(max(x)-min(x))
}
and run

my.range(1:10)
## [1] 9</pre>
```