STATISTICAL TERMINOLOGY

The Basics, Misconceptions, and Pedantises

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Population vs. Sample

Population: describes the sum total of all *existing* values of a variable given a certain research question. This includes non-measured data.

Sample: describes the sum total of all *available* values of a variable for any given analysis. This can only include measured data.

An example:

In an experimental set-up, you rear an ant colony of exactly 10,000 individuals. You are interested in the average mandible strength of ants within the colony.

The problem: You cannot possibly take measurements of all 10,000 individuals.

The solution: Taking measurements on a **Sample** (e.g. 1,000 individuals) from within the **Population** (10,000 individuals).

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Test- vs. Training-Data

This differentiation is only applicable when concerned with *modelling*.

Training Data: describes the subset of the total data which is used to *establish/train* the model.

Test Data: describes the subset of the total data which is used to *test* the performance of the model.

The problem: You have identified a way to model how mandible strength and ant size are interconnected but don't know how to assess the quality of your model (a model will always fit the data it was built on extremely well).

The solution: Split the available data into two non-overlapping subsets of data (**Training** and **Test Data**) and use these separately to build your model and assess its performance.

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Randomness

Randomisation is one of the **most important** practices in biological studies.

A **sampling** procedure is **random** when any member of the *population* has an equal chance of being selected into the *sample*.

Training and *Test Data Sets* are established from the population with the same sense of randomness although there may be exceptions depending on the modelling procedure at hand.

Data collection: Number all units contained within the set-up and sample those units corresponding to random numbers.

In R: Use the `sample()` function to create truly random subsets. Remember to use `set.seed()` to make this step reproducible!

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Stratified Sampling

When do we break *true* **randomness**?.

When a **population** can be divided into distinct categories (i.e. **strata**). These can be regarded as individual sub-populations.

Stratified sampling ensures that all sub-populations are proportionally represented in the final population-sample given their relative size.

```
d
```

```
##   s Freq
## 1 A   50
## 2 B   35
## 3 C   15
```

```
set.seed(42)  # stratified
table(sample(d$s, replace = TRUE, prob = d$Freq, 100))
```

```
##
##  A  B  C
## 45 38 17
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set.seed(42)  # non-stratified
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Unsupervised Approaches

Unsupervised methods are often *used to select* the *most informative X input variables* for *supervised approaches*.

Pre-requisites:

- Only *input variables* are observed.
- *No solution/feedback (output)* is given.

Aims:

- *Divide* the observations into relatively distinct groups.
- *Model* the underlying structure or distribution in the data.

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Supervised Approaches

Supervised methods are often *informed by unsupervised approaches* and used to *gain validated information* about the data.

Pre-requisites:

- Both *predictors* $\mathbf{X}$, and *responses* $\mathbf{Y}$ are observed (there is one y_i for each x_i).
- Data is split into *Training* and *Test Data Sets*.

Aims:

- Learn a *mapping function* f from X to Y.
- *Validate* established function/model.
- Further *prediction* and *inference*.

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Types of Variables

Variables can be classed into a multitude of types. The most common classification system knows:

Categorical Variables

- also known as *Qualitative Variables*
- Scales can be either:
  - Nominal
  - Ordinal

Continuous Variables

- also known as *Quantitative Variables*
- Scales can be either:
  - Discrete
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Categorical Variables

Categorical variables are those variables which **establish and fall into distinct groups and classes**.

Categorical variables:

- can take on a finite number of values
- assign each unit of the population to one of a finite number of groups
- can *sometimes* be ordered

In R, categorical variables usually come up as object type `factor` or `character`.

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Categorical Variables (Examples)

Examples of categorical variables:

- Biome Classifications (e.g. "Boreal Forest", "Tundra", etc.)
- Sex (e.g. "Male", "Female")
- Hierarchy Position (e.g. "α-Individual", "β-Individual", etc.)
- Soil Type (e.g. "Sandy", "Mud", "Permafrost", etc.)
- Leaf Type (e.g. "Compound", "Single Blade", etc.)
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Continuous Variables

Continuous variables are those variables which **establish a range of possible data values**.

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In R, continuous variables usually come up as object type `numeric`.

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Converting Variable Types

Continuous variables can be converted into *categorical variables* via a method called **binning:**

Given a variable range, one can establish however many “bins” as one wants. For example:

- Given a temperature range of $271K - 291K$, there may be 4 bins of equal size:
  - Bin A: $271K \leq X \leq 276K$
  - Bin B: $276K < X \leq 281K$
  - Bin C: $281K < X \leq 286K$
  - Bin D: $286K < X \leq 291K$

Whilst a **continuous variable** can be both *continuous* and *categorical*, a **categorical variable** can only ever be *categorical*!

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Variables On Scales

Another way of classifying variables are the **scales** they are represented on.

Different scales of variables **require different statistical procedures** for analyses!

Variable scales include:

- **Nominal**
- **Binary**
- **Ordinal**
- **Interval**
- **Relation/Ratio**

Some statistics books teach *integer scales* along the above mentioned scales. Some people dispute this and claim these scales to be *ratio scales*.

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Another way of classifying variables are the **scales** they are represented on.

Different scales of variables **require different statistical procedures** for analyses!

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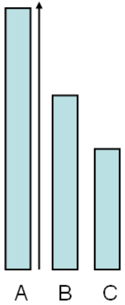
Nominal scales of variables correspond to *categorical variables* which cannot be put into a meaningful order.

- Variables on nominal scales put units into distinct categories
- These variables may be numerical but offer no mathematical interpretation

Examples:

- Petal colour (red, green, blue, etc.)
- Individual IDs



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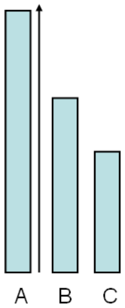

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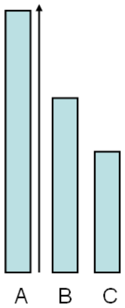

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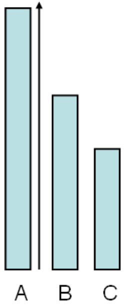

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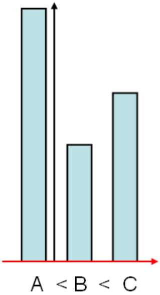

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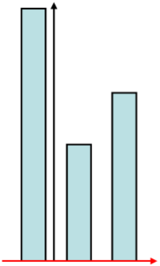

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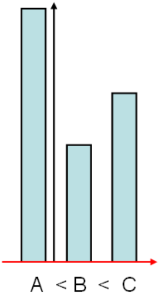

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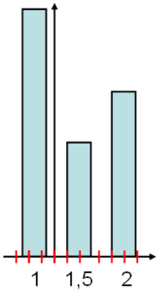

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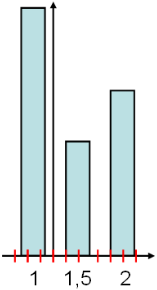

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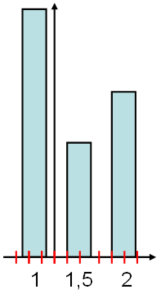

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Examples:

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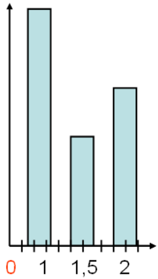

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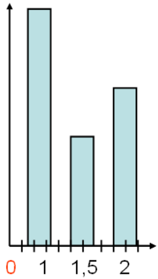

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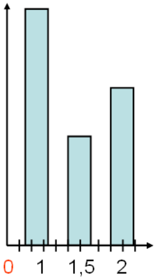

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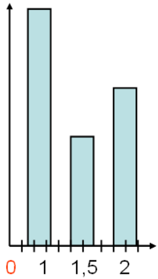

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Confusion Of Units

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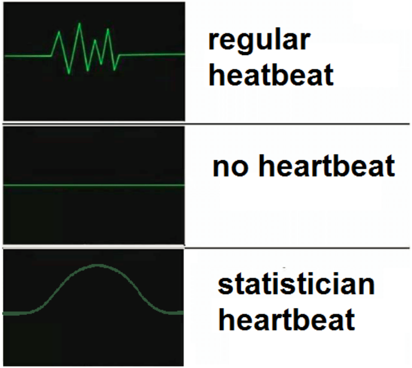

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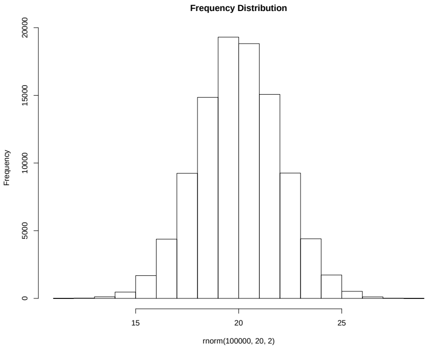
Frequency Distributions

Frequency Distributions:

- *Theory*
  - Simple representations of data value frequencies
  - Can be established for every variable
- *Practice in R*
  - Visualisation via the ‘hist()‘ function

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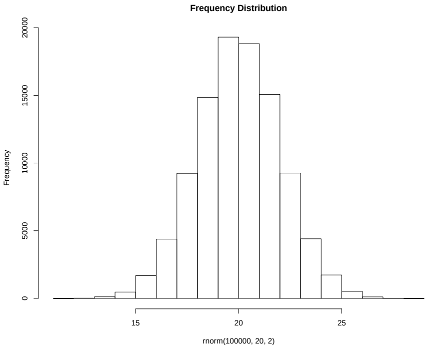


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Probability Density Distributions:

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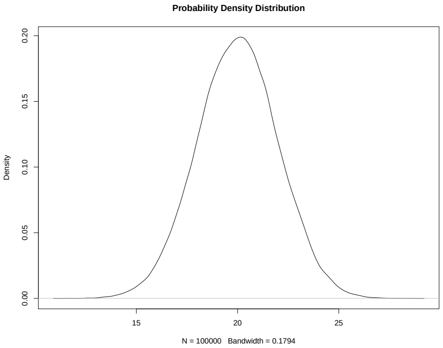


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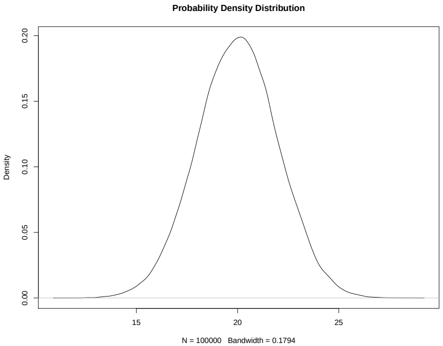


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Probability Density Distributions hold the **majority of importance** in statistics!

A few key points about these distributions:

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- Used to represent real-valued random variables whose distributions are not known
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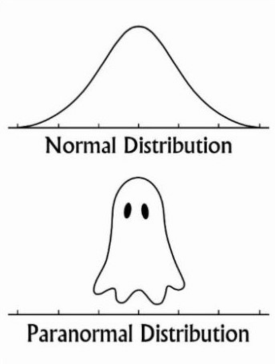

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- Compare the data distribution to the normal distribution

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Using the `shapiro.test()` function:

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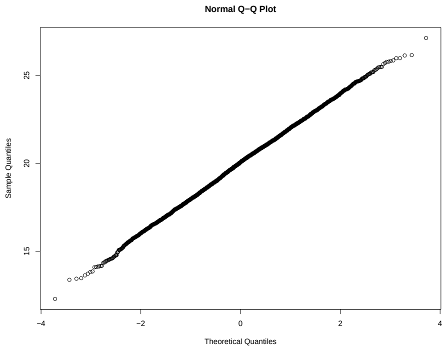

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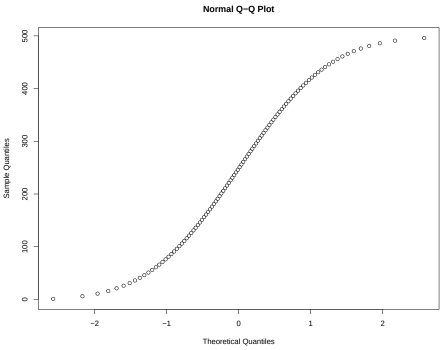

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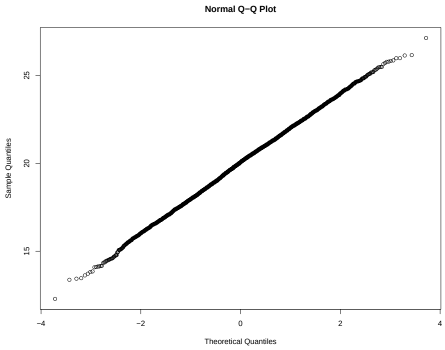

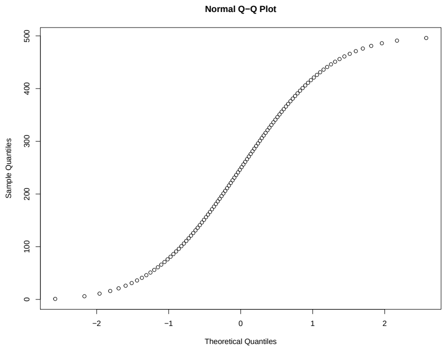

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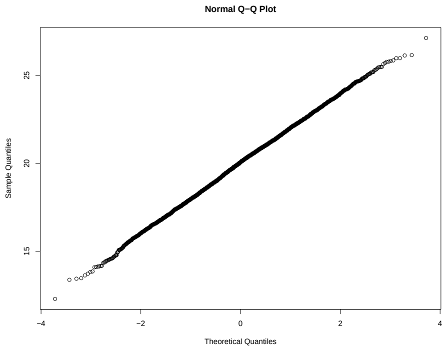

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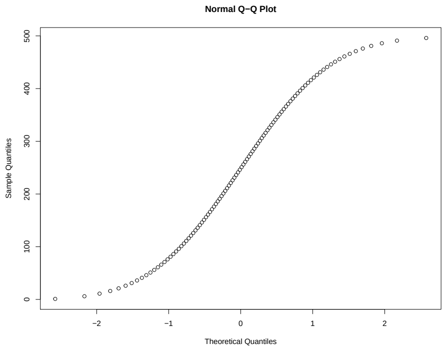

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Binomial Distribution

One of the **more important** distributions. It is applicable to:

- Variables which can only take two possible values (e.g. “states”)
- All records of the variable have the same probability *p* of being in one of the two states

It is made up of three **criteria**:

- p - the "success" probability
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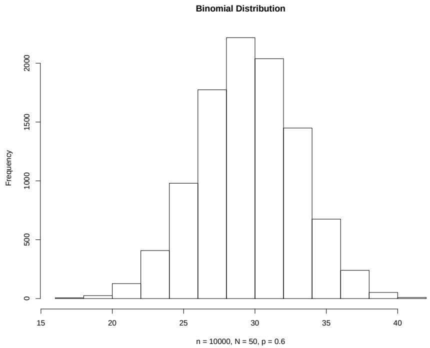

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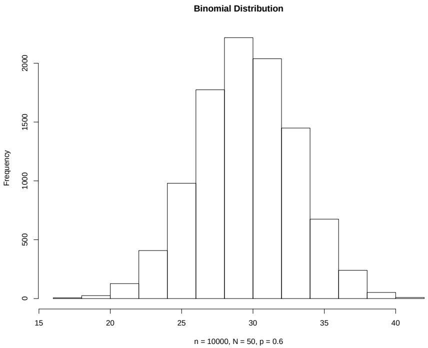

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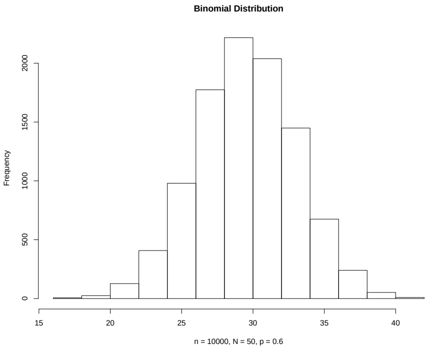

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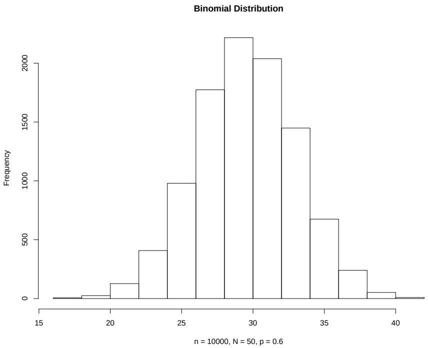

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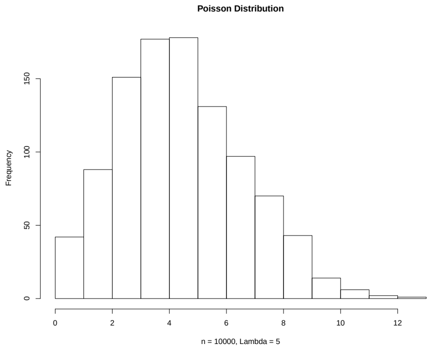
It is made up of two **criteria**:

- λ - the mean (= expectation, average count, intensity) as well as the variance (i.e., variance = mean)
- n - sample size



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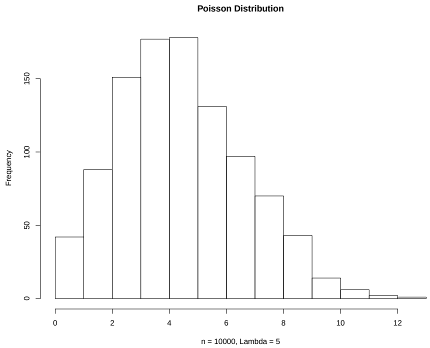

It is made up of two **criteria**:

- λ - the mean (= expectation, average count, intensity) as well as the variance (i.e., variance = mean)
- n - sample size

Poisson Distribution

Another one of the **more important** distributions. It is applicable to:

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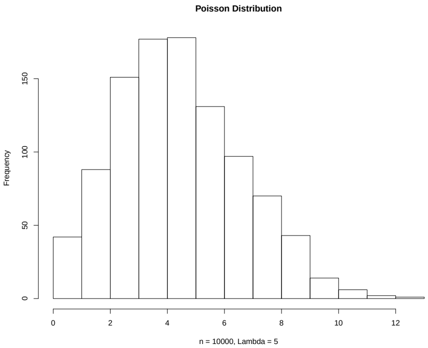

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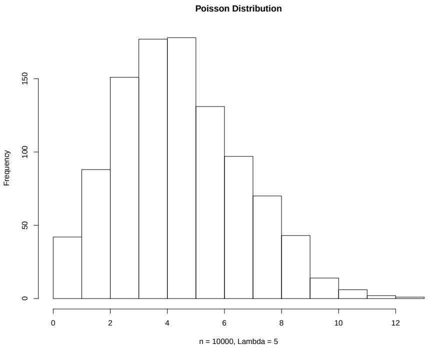

How to Measure Distributions

Not all distributions are created equally.

Distributions can be described via **classic parameters of descriptive statistics:**

- Arithmetic Mean
- Mode
- Median
- Minimum, Maximum, Range
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- Variance
- Standard Deviation
- Quantile Range
- **Skewness**
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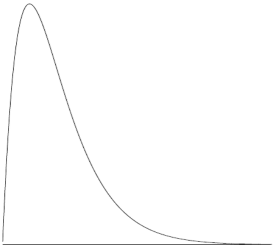
Skewness I

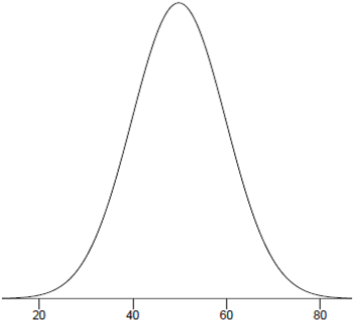
Definition:	Describes the symmetry and relative tail length of distributions.

Positive skew:	Right-hand tail is longer than the left-hand tail
Skew = 0:	Symmetric distribution
Negative skew:	Left-hand tail is longer than the right-hand tail

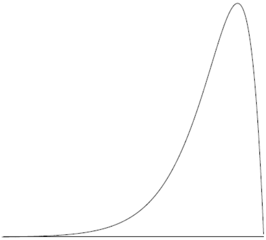
Skewness II



Positive Skew



Symmetric Distribution



Negative Skew

Kurtosis I

Definition:	Describes the evenness/"tailedness" of distributions.

Positive kurtosis:	Short-tailed distribution aka. *leptokurtic*
Kurtosis = 0:	Base representation of a given distribution aka. *mesokurtic*
Negative kurtosis:	Long-tailed distribution aka. *platykurtic*

Kurtosis II