Ministry of Higher Education and Scientific Research
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Course in Bio-statistic

“Steps to choose the right statistical test in scientific research”

From Doctors and Master’s

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Introduction

This introduction describes some typical examples of statistical problems in the medical and biological sciences. Most of the examples come from Brown and Hollander (1978). The techniques needed to solve these problems are discussed in the following chapters.

Examples of statistical problems

Attitude of doctors towards two types of insured

A study conducted at the Stanford University Medical School Pediatric Clinic (Cannon and Remen, 1972) investigated the association between the type of patient insurance and the services offered. The 50% of children who requested an outpatient consultation at the clinic were covered by an assistance program, called Medi-Cal, which benefited from a federal subsidy, while the rest was covered by other sources (private insurance, private payments, etc.). The question asked was, is the service offered to Medi-Cal and Non Medi-Cal patients the same?

Indeed, different hypotheses could be formulated:

1. The Medi-Cal patient receives more diagnostic tests on average because the cost of the medical procedure is fully covered by his insurance;
2. The Medi-Cal patient receives fewer tests because he has little interest in developing the diagnosis;
3. Medi-Cal and Non Medi-Cal patients receive different treatments because the Medi-Cal patient follows less of his doctor's prescriptions than the Non Medi-Cal patient. It is then preferable to resort to hospitalization rather than outpatient treatment, or long-acting injections rather than oral and daily treatment.

The question being complex, it was necessary to simplify it and reduce the study to well documented cases with a clear diagnosis and standard treatment. In this sample, Medi-Cal patients receive more intramuscular injections than Non Medi-Cal patients. The original question then becomes a statistical problem: is this result valid for all (not observed) cases of pneumonia? Could the same table be obtained by the simple (random) selection mechanism of the sample?

In order to answer this question:

– compare two rates in a sample;

– check or test if there is a difference between the corresponding rates for the entire Stanford Medi-Cal and Non Medi-Cal patient population.

Important questions arise in all human activities: they often lead to decisions that scientists, managers, politicians, etc. must take on the basis of limited information in the form of data. How is that information developed and how can it be used? Those are statistical questions. The statistical approach can be compared to the search for a solution in a police enigma. The first step is exploratory data analysis.

Exploratory and descriptive analysis

At this point, the analyst tries to explore and describe the content of his data. It represents them in such a way as to see trends and discover structures. The methods used at this stage are relatively simple. For example, we are interested in knowing in what interval the majority of the data is located where the most frequent values are; we represent the possible association between two observed quantities, etc. The necessary instruments are often graphic but the distribution of the data is also characterized by some numerical values called statistical summary.

Since the inference is based on random samples, it is necessary to use the probability calculation to measure the uncertainty of the obtained results, for example, to calculate the probability of error in a statistical test.

I-Statistics(s) and Probability(s)

We will start by defining important terms and concepts.

I.1- Statistics

The term statistical refers to both a set of observation data and the activity of collecting, processing and interpreting them. Statistical terms (plural) include several distinct concepts:

1. On the one hand, the census of quantities of interest such as the number of inhabitants of a country, the average income per inhabitant, the number of HIV positive persons in the French population. We see that the fundamental notion that emerges from this enumeration is that of Population. A population is a set of objects, living beings or abstract objects (set of hands of 5 cards dealt at bridge...) of the same nature.
2. Statistics as science is concerned with the properties of natural populations. More specifically, it deals with numbers obtained by counting or measuring the properties of a population. This population of objects must also be subjected to variability, which is due to many unknown factors (for the populations of biological objects that interest us these factors are genetic factors and environmental factors).
3. To these two definitions of the term statistics (plural) must be added the term statistics (singular) which defines any quantity calculated from observations. This may be the largest value of the statistical series of interest, the difference between the largest and smallest, the value of the arithmetic mean of these values, etc.

I.2- Population and Sample

Population P is generally a very large, if not infinite, set of individuals or objects of the same nature. All the doctors in France constitute a population, as well as all the possible results of the lottery draw. A population may therefore be real or fictitious.

It is usually impossible, or too expensive, to study all the individuals constituting a population; we then work on a part of the population called a sample. In order for a sample to study the variability of characteristics of interest to the population, it must be properly selected. The representative sample will be considered if the individuals making it were drawn at Exit 1 in the population. For example, if we want to determine the "average" characteristics of the weight and height of male preterm babies, we will randomly draw a number of subjects among the preterm births of the year.

Each individual or statistical unit, belonging to a population is described by a set of characteristics called variables or characters. These variables can be quantitative (numerical) or qualitative (non-digital):

Quantitative can be classified into continuous variables (height, weight) or discrete variables (number of children in a family)

Qualitative can be classified into categorical (eye colour) or ordinal variables (intensity of pain classified as zero, low, medium, significant).

I.3- Statistics and Probability

The theory (or calculation) of probabilities is a branch of mathematics that allows to model the phenomena where the chance intervenes (initially developed in relation to gambling, then gradually extended to all experimental sciences, including physics and biology). This theory allows building models of these phenomena and allows the calculation: It is from a probabilistic model of a game of chance such as the dice game that we can predict the frequencies of occurrence of events such as the number of times we obtain a pair value by throwing a dice a large number of times. The elements of probability calculation essential to the understanding of statistics will be treated in the first part of the course. Underlying the notion of statistics is the notion of Population whose properties we want to know (more precisely the regularities), allowing in particular to know whether two populations are identical or not. This is the case of the therapeutic trials framework, where we consider two populations (patients treated with drug A or with drug B) which we want to know if they differ or not (this is the simplest case of clinical trials). To do this it is necessary to model populations, using probabilistic models. A model of this type is for example to consider that the size of individuals follows a Gaussian distribution. From this model we can calculate the properties of samples; this is called a deduction that goes from the model to the experiment. Conversely, considering a sample of a population we can try to reconstruct the population model. This approach is based on the usual scientific approach. The scientist is able, using mathematics, to predict the behaviour of a given model (it is for example a «law» of physics): it is the deductive approach. On the other hand, observing experimental facts he will try to identify general properties of the observed phenomenon which he will generally represent in the form of a model (all the laws of physics and chemistry are the most general possible mathematical models of experimental facts): this is the inductive construction of theory. This general approach goes further because the model allows predicting experiments not carried out. If the predictions thus made are contradictory with the experimental results then we can with certainty refute the model (we also say that we falsified it); otherwise we keep the model but we are not sure that it is «true». In other words, at the end of such a test, we can only be certain if we have found evidence to refute the model. We shall see later that this approach is exactly reflected in the statistical approach, particularly in the field of testing.

I.4- General Definitions

Statistics: The art of collecting, analysing and interpreting "data" to assess the "reliability" of decisions based on that "data" – one way of representing and structuring available knowledge in a field.

• **Biostatistics**: application of statistics to biological problems.

Data (value) = result of observation of an individual.

- Observe = reduce an infinitely complex object to a limited number of features.

• Choosing the "characteristic" well already reflects knowledge about the individual.

• Observing requires a measuring instrument

• Most often, the «characteristic» is interesting only if it can be observed on several individuals. Generally, it is not strictly identical from one individual to another. We will therefore talk about a variable, and we will say that the observed data is the "achievement" of this variable for the observed individual.

- **Analyse**: **Descriptive statistics**: The art of organizing, presenting and summarizing data acquired on representative samples of a population.

– **Interpret**: **Interpretive or inferential statistics**: The art of inferring, from data acquired from representative samples of a population, the behaviour of variables of interest in the population and making valid decisions in the population, based on observations in samples.

• Mastering the risk of error in inferences and decisions (assessing reliability).

- This will require a detour through the "probability" domain.

Population: These are all the "individuals" about whom we wish to infer decisions

- It is most often defined by a property with one or more variables:

• All the French

• All new burns born to diabetic mothers

- Decisions will be based on observations of variables of interest in this population

Samples: With exception (very small population size), it is impossible to measure the variable of interest on all individuals in the population

• **A sample is a subset** of this population on which the variable of interest can be observed, and these observations can be used to infer decisions about any individual in the population. The sample size is the number of individuals in the sample.

Random (representative) sampling: For valid inference of decisions, the sample must be randomized ("randomized").

- Each individual in the population has the same "chance" to be included in the sample.
- Keeping an individual in the sample does not affect another individual's "chance" of being selected.

• Ideally, assign a number to each individual, and draw lots with a random number generator. In practice, more complex… we will always assume that the samples we are talking about have been "randomized".

Parameters: A parameter is a quantity providing summarized information on the variable of interest (example we will review: the average).

• A parameter can be measured in a sample

• A parameter can be estimated in the population, based on observations from the sample

II- Statistical tests Importance

II.1- Statistical tests

Statistical tests are of various types, depending upon the nature of the study. Statistical tests provide a method for making quantitative decisions about a particular sample. Statistical tests mainly test the hypothesis that is made about the significance of an observed sample.

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Statistical tests are used in hypothesis testing. They can be used to:

Determine whether a predictor variable has a statistically significant relationship with an outcome variable.

Estimate the difference between two or more groups.

Statistical tests assume a null hypothesis of no relationship or no difference between groups. Then they determine whether the observed data fall outside of the range of values predicted by the null hypothesis.

If you already know what types of variables you're dealing with, you can use the flowchart to choose the right statistical test for your data.

II.2-What does a statistical test do?

Statistical tests work by calculating a test statistic – a number that describes how much the relationship between variables in your test differs from the null hypothesis of no relationship.

It then calculates a *p* value (probability value). The *p*-value estimates how likely it is that you would see the difference described by the test statistic if the null hypothesis of no relationship were true.

If the value of the test statistic is more extreme than the statistic calculated from the null hypothesis, then you can infer a statistically significant relationship between the predictor and outcome variables.

If the value of the test statistic is less extreme than the one calculated from the null hypothesis, then you can infer no statistically significant relationship between the predictor and outcome variables.

II.3-When to perform a statistical test

You can perform statistical tests on data that have been collected in a statistically valid manner – either through an experiment, or through observations made using probability sampling methods.

For a statistical test to be valid, your sample size needs to be large enough to approximate the true distribution of the population being studied.

To determine which statistical test to use, you need to know:

- Whether your data meets certain assumptions.
- The types of variables that you're dealing with.

II.4-Statistical assumptions

Statistical tests make some common assumptions about the data they are testing:

1. **Independence of observations** (a.k.a. no autocorrelation): The observations/variables you include in your test are not related (for example, multiple measurements of a single test subject are not independent, while measurements of multiple different test subjects are independent).
2. **Homogeneity of variance**: the variance within each group being compared is similar among all groups. If one group has much more variation than others, it will limit the test's effectiveness.
3. **Normality of data**: the data follows a normal distribution (a.k.a. a bell curve). This assumption applies only to quantitative data.

If your data do not meet the assumptions of normality or homogeneity of variance, you may be able to perform a nonparametric statistical test, which allows you to make comparisons without any assumptions about the data distribution.

If your data do not meet the assumption of independence of observations, you may be able to use a test that accounts for structure in your data (repeated-measures tests or tests that include blocking variables).

Types of variables

The types of variables you have usually determine what type of statistical test you can use.

Quantitative variables represent amounts of things (e.g. the number of trees in a forest). Types of quantitative variables include:

- **Continuous** (aka ratio variables): represent measures and can usually be divided into units smaller than one (e.g. 0.75 grams).
- **Discrete** (aka integer variables): represent counts and usually can't be divided into units smaller than one (e.g. 1 tree).

Categorical variables represent groupings of things (e.g. the different tree species in a forest). Types of categorical variables include:

- **Ordinal**: represent data with an order (e.g. rankings).
- **Nominal**: represent group names (e.g. brands or species names).
- **Binary**: represent data with a yes/no or 1/0 outcome (e.g. win or lose).

Choose the test that fits the types of predictor and outcome variables you have collected (if you are doing an experiment, these are the independent and dependent variables). Consult the tables below to see which test best matches your variables.

Conclusion:

Statistical tests are of great importance, and we will recognize them through a number of points, the most important of which are:

1. Statistical tests in scientific research contribute to the analysis of all data.

2. Contribute to accurate and simple presentation of all data.

3. Arrive at a set of correct outcomes for the community level.

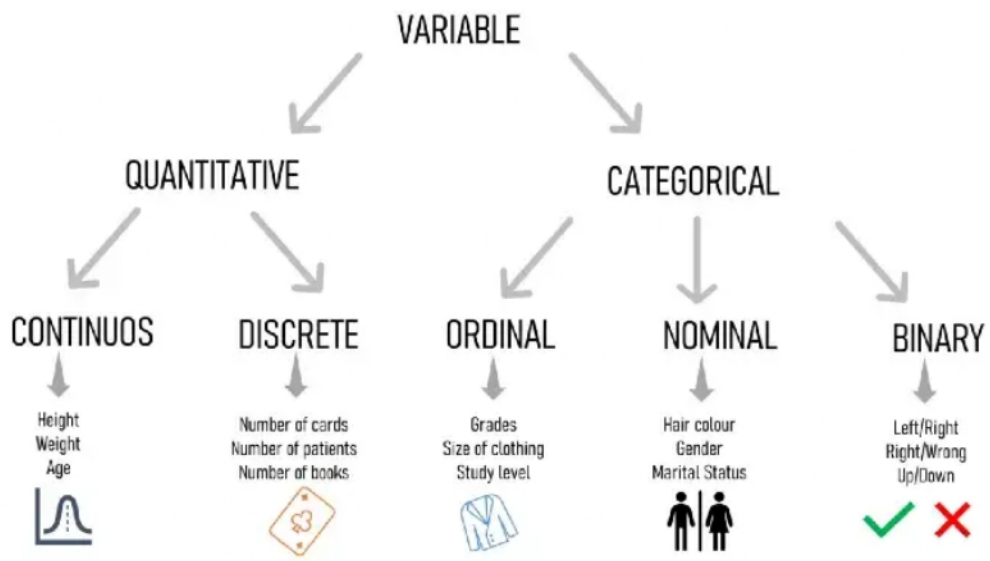

Figure 01: Types of variables summary

III- Steps to choose the statistical test

Statistics is all about data. Data alone is not interesting. It is the interpretation of the data that we are interested in.

In Statistics, one very important thing is statistical testing, if statistics "is the interpretation of the data", statistical testing can be considered as the "formal procedure for investigating our ideas about the world".

In other words, whenever we want to make claims about the distribution of data or whether one set of results are different from another set of results, data scientists must rely on hypothesis testing.

There are five main steps that make it easier to choose the right statistical test for research:

- Hypotheses testing
- Determine the type of statistical assumptions.
- Distinguishing between Parametric and Non-Parametric Tests
- Choosing between Parametric and Non-Parametric Tests.
- Determining levels of statistical significance.

III.1- Hypotheses testing

Using Hypothesis Testing, we try to interpret or draw conclusions about the population using sample data, evaluating two mutually exclusive statements about a population to determine which statement is best supported by the sample data.

There are five main steps in hypothesis testing:

Step 1) State your hypothesis as a Null (H_o) and Alternate (Ha) hypothesis.

Step 2) Choose a significance level (also called alpha or α).

Step 3) Collect data in a way designed to test the hypothesis.

Step 4) Perform an appropriate statistical test: compute the p-value and compare from the test to the significance level.

Step 5) Decide whether to "Reject" the null hypothesis (H_o) or "Fail to reject" the null hypothesis (H_o).

Note: Though the specific details might vary the procedure you will use when testing a hypothesis will always follow some version of these steps.

If you want to further understand hypothesis testing, I would highly recommend these two great posts on Hypothesis testing.

III.2- Statistical assumptions

Statistical tests make some common assumptions about the data being tested (If these assumptions are violated then the test may not be valid: e.g. the resulting p-value may not be correct)

1. **Independence of observations**: the observations/variables you include in your test should not be related(e.g. several tests from a same test subject are not independent, while several tests from multiple different test subjects are independent)
2. **Homogeneity of variance**: the "variance" within each group is being compared should be similar to the rest of the group variance. If a group has a bigger variance than the other(s) this will limit the test's effectiveness.
3. **Normality of data**: the data follows a normal distribution, normality means that the distribution of the test is normally distributed (or bell-shaped) with mean 0, with 1 standard deviation and a symmetric bell-shaped curve.

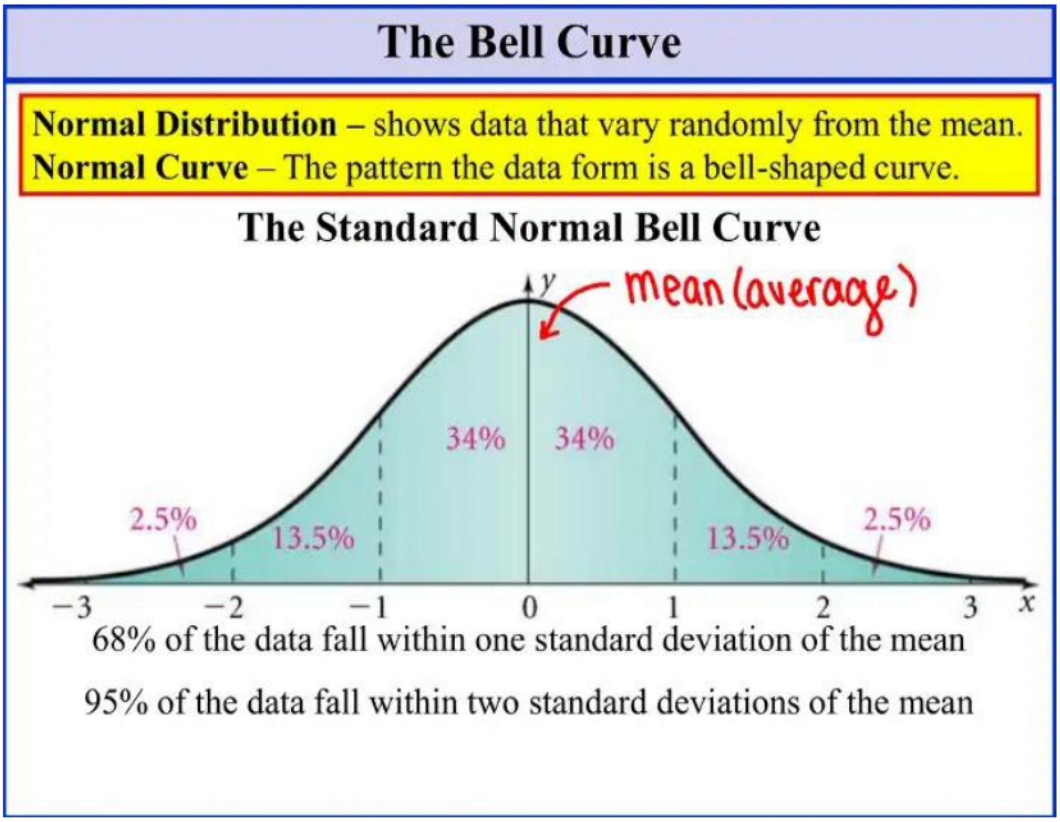

Figure 02: Standard Normal Bell Curve

III.3- Distinguishing between Parametric and Non-Parametric Tests (Normality testing)

Normal law (or Laplace-Gauss law or Gauss law)

Normal distribution is a theoretical distribution, in the sense that it is a mathematical idealization that never exactly meets in nature. But many distributions actually observed are similar and have this famous form of «bell» (many individuals around the average, less and less as we move away from it and this in a symmetrical way).

On the other hand, it is widely used in inferential statistics: we will see in particular that an average calculated on a sample is a random variable. Which tends to follow a normal law when the sample size increases, even if the initial population has a completely different distribution?

Its shape: the bell curve

The normal law of parameters m and σ, noted N(m; σ), is defined on R by the density:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-m}{\sigma}\right)^2}$$

Whose graphic representation is as follows?

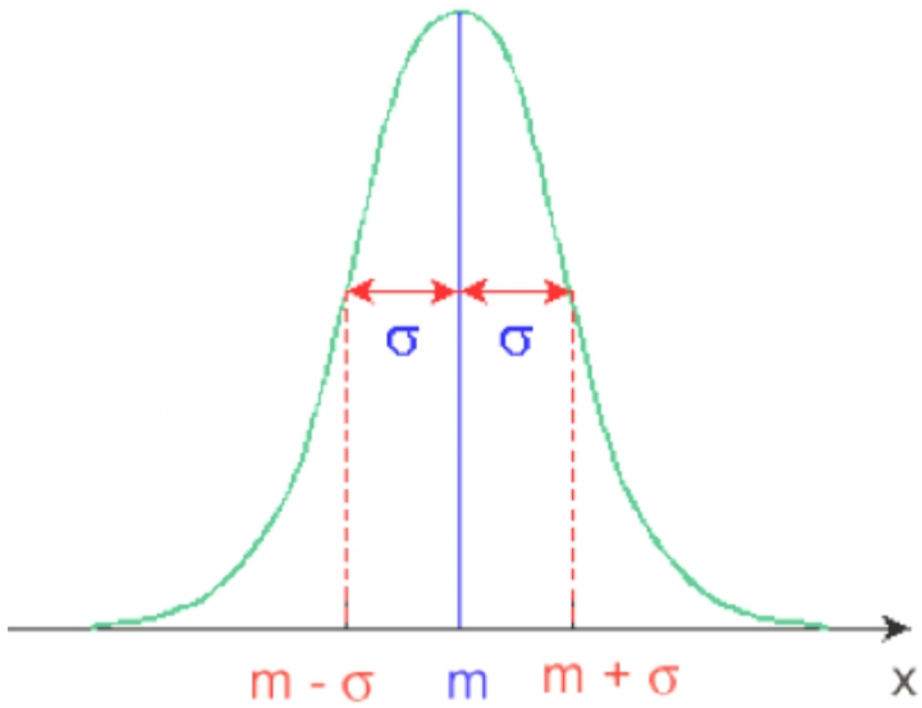

Figure 03: Standard Normal

III.4- Choosing between Parametric and Non-Parametric Tests

III.4.1- Parametric tests

Parametric tests are the ones that can only be run with data that stick with the *"three statistical assumptions"* mentioned above. The most common types of parametric tests are divided into three categories.

Regression tests:

These tests are used test cause-and-effect relationships**,** if the change in one or more continuous variable predicts change in another variable.

- **Simple linear regression:** tests how a change in the predictor variable predicts the level of change in the outcome variable.
- **Multiple linear regression:** tests how changes in the combination of two or more predictor variables predict the level of change in the outcome variable
- **Logistic regression:** is used to describe data and to explain the relationship between one dependent (binary) variable and one or more nominal, ordinal, interval or ratio-level independent variable(s).

Comparison tests:

These tests look for the difference between the means of variables: Comparison of Means.

- **T-tests** are used when comparing the means of precisely two groups (e.g. the average heights of men and women).
- **Independent t-test**: Tests the difference between the *same variable from different populations* (e.g., comparing dogs to cats)
- **ANOVA** and **MANOVA** tests are used to compare the means of more than two groups or more (e.g. the average weights of children, teenagers, and adults).

Correlation tests:

These tests look for an association between variable checking whether two variables are related.

- **Pearson Correlation:** Tests for the strength of the association between two continuous variables.
- **Spearman Correlation:** Tests for the strength of the association between two ordinal variables (it does not rely on the assumption of normally distributed data)

- **Chi-Square Test:** Tests for the strength of the association between two categorical variables.

Regression Tests

	Predictor Variable	Output Variable	Example
Single Linear Regression	• Continuous • 1 predictor	• Continuous • 1 outcome	What is the effect of height on longevity?
Multiple Linear Regression	• Continuous • 2 or more predictors	• Continuous • 1 outcome	What is the effect of income and number of children on longevity?
Logistic Regression	• Continuous • 1 predictor or more	• Binary • 1 predictor	What is the effect of drug dosage on the survival of a test subject?

Comparison Tests

	Predictor Variable	Output Variable	Example
Paired t-test	• Categorical • 1 predictor	• Quantitative • Groups come from the same population	"What is the effect of two different training programs on the average performance for athletes from the same team?"
Independent t-test	• Categorical • 1 predictor	• Quantitative • Groups come from different populations	"What is the difference in average exam scores for students from two different colleges?"
ANOVA	• Categorical • 1 predictor or more	• Quantitative • 1 outcome	"What is the difference in average pain levels among post-surgical patients given three different painkillers?"
MANOVA	• Categorical • 1 predictor or more	• Quantitative • 2 or more outcomes	"What is the effect of flower species on petal length, petal width, and stem length?"

Correlation Tests

	Predictor Variable	Output Variable	Example
Pearson	• Continuous	• Continuous	How are pressure and temperature related?
Chi-Square	• Categorical	• Categorical	How is membership in a sports team related to membership in a drama club among high school students?

Figure 04: Parametric tests summary

Flowchart: Choosing a parametric test

This flowchart will help you choose among the above described parametric tests. For nonparametric alternatives, check the following section.

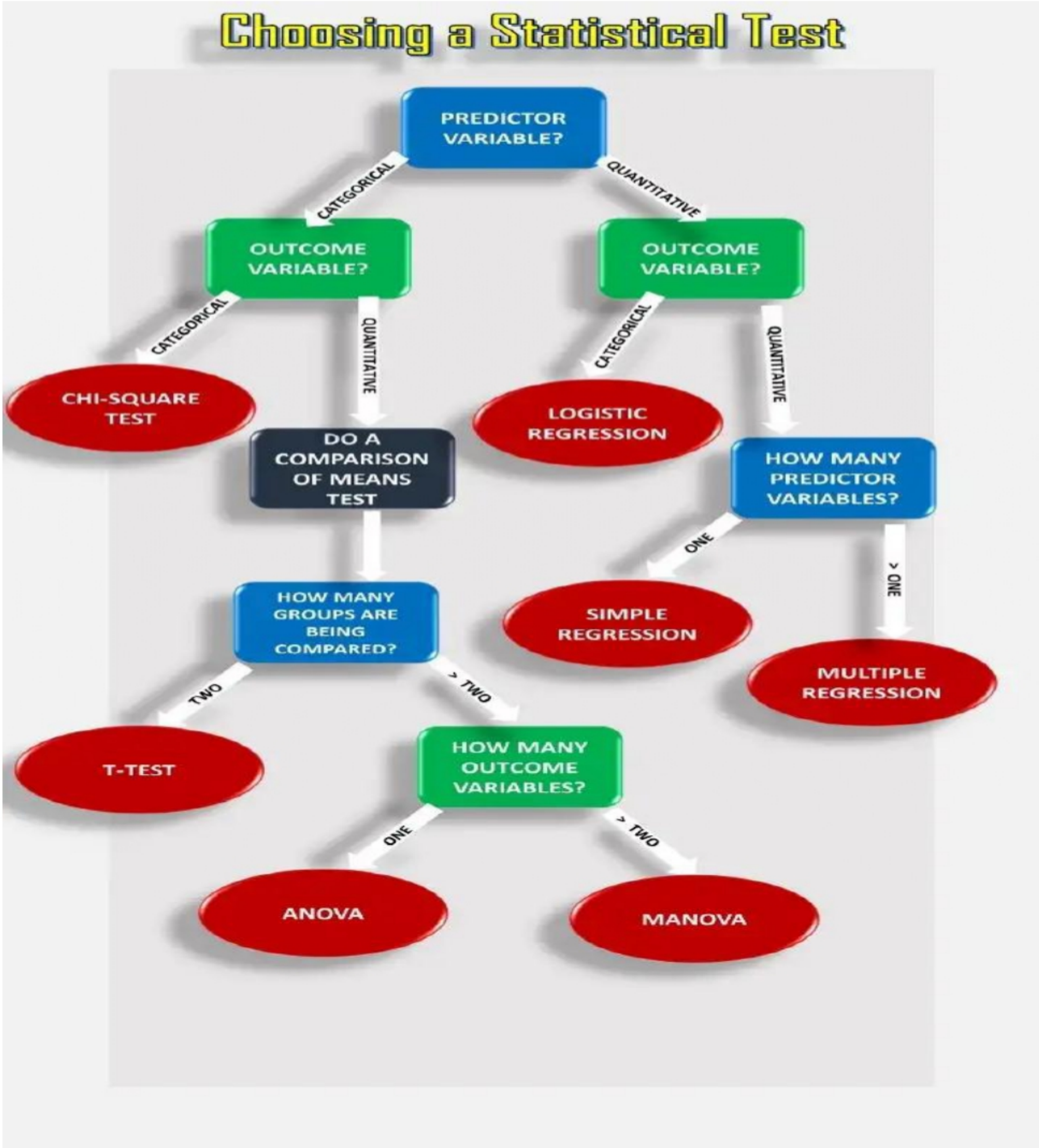

Figure 05: Parametric tests Flowchart

III.4.2- Dealing with non- normal distributions

Although the normal distribution takes centre part in statistics, many processes follow non-normal distributions. Many datasets naturally fit a non-normal model:

-The number of accidents tends to fit a "Poisson distribution"

-The Lifetimes of products usually fit a "Weibull distribution".

Example of Non-Normal Distributions

1. Beta Distribution.
2. Exponential Distribution.
3. Gamma Distribution.
4. Inverse Gamma Distribution.
5. Log-Normal Distribution.
6. Logistic Distribution.
7. Maxwell-Boltzmann Distribution.
8. Poisson Distribution.
9. Skewed Distribution.
10. Symmetric Distribution.
11. Uniform Distribution.
12. Unimodal Distribution.
13. Weibull Distribution.

Well then, how do we deal with non-Normal-Distributions?

When your data is supposed to fit a normal distribution but doesn't, we could do a few things to handle them:

- We may still be able to run parametric tests if your sample size is large enough (usually over 20 items) and try to interpret the results accordingly.
- We may choose to transform the data with different statistical techniques, forcing it to fit a normal distribution.
- If the sample size is small, skewed or if it represents another distribution type, you might run a **non-parametric test**.

III.4.3- Non-Parametric Tests

Non-parametric tests (figure below) don't make as many assumptions about the data and are useful when one or more of the three statistical assumptions are violated.

Note that: The inferences that non-parametric tests make aren't as strong as the parametric tests.

	Predictor Variable	Output Variable	Use in place of
Spearman	• Ordinal	• Ordinal	Regression & Correlation tests
Sign-test	• Categorical	• Quantitative	T-test
Kruskal-Wallis	• Categorical • 3 or more groups	• Quantitative	ANOVA
ANOSIM	• Categorical • 3 or more groups	• Quantitative • 2 or more outcomes	MANOVA
Wilcoxon Rank-Sum test	• Categorical • 2 groups	• Quantitative • Groups come from different populations	Independent t-test
Wilcoxon Signed-rank test	• Categorical • 2 groups	• Quantitative • Groups come from the same population	Paired t-test

Figure 05: Non-parametric tests Flowchart

III.5- Determining levels of statistical significance

The significance level, also known as alpha or α, is a measure of the strength of the evidence that must be present in your sample before you will reject the null hypothesis and conclude that the effect is statistically significant. The researcher determines the significance level before conducting the experiment.

The significance level is the probability of rejecting the null hypothesis when it is true. For example, a significance level of 0.05 indicates a 5% risk of concluding that a difference exists when there is no actual difference. Lower significance levels indicate that you require stronger evidence before you will reject the null hypothesis.

Use significance levels during hypothesis testing to help you determine which hypothesis the data support. Compare your p-value to your significance level. If the p-value is less than your significance level, you can reject the null hypothesis and conclude that the effect is statistically significant. In other words, the evidence in your sample is strong enough to be able to reject the null hypothesis at the population level.

How to calculate statistical significance (and its importance)

If you're trying to determine the effectiveness of something, consider calculating statistical significance. Though it's known for being taught in statistics coursework, it can be used for a variety of different industries including business.

In this article, we define statistical significance, its importance and how to calculate it by hand.

What is statistical significance?

Statistical significance refers to the likelihood that a relationship between two or more variables is not caused by random chance. In essence, it's a way of proving the reliability of a certain statistic. Its two main components are sample size and effect size. In the use of statistical hypothesis testing, a data set's result can be deemed statistically significant if you have reached a certain level of confidence in the result. In statistical hypothesis testing, this means the hypothesis is unlikely to have occurred given the null hypothesis. According to a null hypothesis, there is no relationship between the variables in question.

Why is statistical significance important?

In regards to business, statistical significance is important because it helps you know that the changes you've implemented can be positively attributed to various metrics. For example, if you've recently implemented a new application to help your office work more efficiently, statistical significance provides you with the confidence in knowing that it made a positive impact on your company's overall workflow. That is, the app's impact was statistically significant and provided value. If it turns out the app wasn't statistically significant, this means your business dollars and the app are at risk. Make sure to measure the statistical significance for every result to get a more comprehensive calculation and result.

To help you make business decisions in the future, consider using business relevance along with statistical significance. This will ensure your decisions are not based on statistical significance alone.

How to calculate statistical significance:

Calculating the statistical significance is rather extensive if you calculate it by hand and this is why it's typically calculated using a calculator. When you calculate it by hand, however, it will help you more fully understand the concept. Here are the steps for calculating statistical significance:

1. Create a null hypothesis
2. Create an alternative hypothesis
3. Determine the significance level
4. Decide on the type of test you'll use
5. Perform a power analysis to find out your sample size
6. Calculate the standard deviation
7. Use the standard error formula
8. Determine the t-score
9. Find the degrees of freedom
10. Use a t-table

1. Create a null hypothesis

The first step in calculating statistical significance is to determine your null hypothesis. Your null hypothesis should state that there is no significant difference between the sets of data you're using. Keep in mind that you don't need to believe the null hypothesis.

2. Create an alternative hypothesis

Next, create an alternative hypothesis. Typically, your alternative hypothesis is the opposite of your null hypothesis since it'll state that there is, in fact, a statistically significant relationship between your data sets.

3. Determine the significance level

Your next step involves determining the significance level or rather, the alpha. This refers to the likelihood of rejecting the null hypothesis even when it's true. A common alpha is 0.05 or five percent.

4. Decide on the type of test you'll use

Next, you'll need to determine if you'll use a one-tailed test or a two-tailed test. Whereas the critical area of distribution is one-sided in a one-tailed test, it's two-sided in a two-tailed test. In other words, one-tailed tests analyze the relationship between two variables in one direction and two-tailed tests analyze the relationship between two variables in two directions. If the sample you're using lands within the one-sided critical area, the alternative hypothesis is considered true.

5. Perform a power analysis to find out your sample size

You'll then need to do a power analysis to determine your sample size. A power analysis involves the effect size, sample size, significance level and statistical power. For this step, consider using a calculator. This type of analysis allows you to see the sample size you'll need to determine the effect of a given test within a degree of confidence. In other words, it'll let you know what sample size is suitable to determine statistical significance. For example, if your sample size ends up being too small, it won't give you an accurate result.

6. Calculate the standard deviation

Next, you'll need to calculate the standard deviation. To this, you'll use the following formula:

standard deviation = $\sqrt{((\sum|x-\mu|^{2}) / (N-1))}$

where:

$\sum$ = the sum of the data

x = individual data

μ = the data's mean for each group

N = the total sample

Performing this calculation will let you know how to spread out your measurements are about the mean or expected value. If you have more than one sample group, you'll also need to determine the variance between the sample groups.

7. Use the standard error formula

Next, you'll need to use the standard error formula. For our purposes, let's say you have two standard deviations for your two groups. The standard error formula is as follows:

standard error = $\sqrt{((s1/N1) + (s2/N2))}$

where:

s1 = the standard deviation of your first group

N1 = group one's sample size

s2 = the standard deviation of your second group

N2 = group two's sample size

8. Determine t-score

For the next step, you'll need to find the t-score. The equation for this is as follows:

$t = ((\mu 1 - \mu 2) / (sd))$

where:

t = the t-score

$\mu 1$ = group one's average

$\mu 2$ = group two's average

sd = standard error

9. Find the degrees of freedom

Next, you'll need to determine the degrees of freedom. The formula for this is as follows:

degrees of freedom = (s1 + s2) - 2

where:

s1 = samples of group 1

s2 = samples of group 2

10. Use a t-table

Finally, you'll calculate the statistical significance using a t-table. Start by looking at the left side of your degrees of freedom and find your variance. Then, go upward to see the p-values. Compare the p-value to the significance level or rather, the alpha. Remember that a p-value less than 0.05 are considered statistically significant.

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