What are the Differences Between Common Statistical Tests?

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Statistics are essential components of quantitative (and qualitative) research that we all should know. We have read through numerous lectures on the subject, and we know that we need to understand it and really should by now, even if only to not appear un-knowledgeable at journal club meetings. Still many people skip the section on statistical analysis when reading papers. Sometimes it feels that only those who have performed full time research really understand statistics - and not even then if they were lucky enough to have a statistician on their team. As part of our series of research tutorials we would now like to remove some of the mystery surrounding the art of statistics. Let’s start with the raw data…

What’s the difference between qualitative and quantitative data? As you begin your analysis you will always have a body of raw data which you can then use to reject or accept a null hypothesis. (Remember the Null Hypothesis? It is the chance that there is no difference between the groups being compared.) Before deciding which test you are going to use, you need to first decide what kind of data you are going to collect. Data are either qualitative (e.g., colour of hair, type of job, place of birth, “qualitative information”) or quantitative (e.g., BP readings, serum bilirubin levels, birth weight: quantities, numbers). While that seems relatively easy, some people will try and confuse you by referring to qualitative data as categorical or to quantitative data as numerical. We are going to keep it simple, and we suggest that you stick with the simple subtypes and then take it from there.

What’s the difference between parametric and non-parametric data? Remember the famous Gaussian curve of the normal distribution? If not, look at Figure 1, and it will immediately spring to mind again. A normal distribution is symmetrically distributed around the mean with a bell-shaped curve. If your data are normally distributed, then you can use tests based on the normal distribution (such as the t-test: more on this later); if the data are not normally distributed (i.e., non-parametric, or skewed) then you can either transform to normal (which is not that hard) or use non-parametric tests. Transformation means using specific statistical tools to convert “not-normally” distributed data to normally distributed data, e.g., data that are positively skewed (i.e., skewed to the right) might be transformed by getting the logarithmic of each individual data in the dataset. (However this is risky as the hypothesis being tested will also change).

What’s the difference between average, mean, mode and median? Primary level maths taught us all the meaning of the term “average”. The mean, mode and median may be different numbers but all represent the average value of data. Essentially, the mean is the arithmetic mean (the sum of all the values divided by the number of values), the median is the middle number in a series of numbers (thus, dividing the distribution in half), and the mode is the value that occurs most often (I think of it as being fashionable, or “in mode”, so it is repeated most often). Here are a couple of examples, from this group of numbers, or raw data. This could be ages, or grammes of medication required to get an effect, or...
number of times that we had to learn statistics before we understood it.

5 6 7 9 10 11 15 16 17 17 17 19 20 23 25 30

In this series of numbers, the mean is 13.58, the median is 17 and the mode is also 17. This illustrates one way of deciding whether information is normally distributed or not: in a bell shaped curve the median, mode and mean are all the same. Take this one more step: when describing normally distributed data, the mean is conventionally used to describe the average value (with the confidence intervals), whereas the median is used (with its range or, preferably, interquartile range) in non-parametric data. This means that if you are reading a paper, and the authors describe the data as non-parametric but use the mean and confidence intervals, then they do not know what they are talking about. (How impressive would it be to point that error out in front of your lecturer or consultant?). More usually, when a paper uses a mean and confidence interval then they are saying indirectly that the data are normally distributed.

What's the difference between a t-test and Mann-Whitney U test (and why is it important anyway?) Once you have decided what the data are (qualitative versus quantitative, normally distributed versus non-parametric) you can decide what test to use (or when reading a paper whether they should have used that test in the first place). The simplest example is quantitative data. Often statistical tests try to compare two groups. If these groups are normally distributed a t-test is used, whereas when they are non-parametric a Mann-Whitney U test is used. If more than two groups are being compared another test is introduced, while for normally distributed data analysis of variance (ANOVA) is used. Another test that is often used in papers is the chi-squared ($\chi^2$) test, which compares proportions (hence its full name: the $\chi^2$ test of proportions). Essentially this compares the proportions in two groups: are there more asthmatics in group A or B? Or more women in the cases or controls?

What's the difference between an odds ratio and a relative risk? This is another two terms that are often confused or considered to be synonymous. Let us explain these mathematically first, with reference to Table 1.

<table>
<thead>
<tr>
<th>Table 1: Outcome One vs Outcome Two</th>
<th>Outcome One</th>
<th>Outcome Two</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cases</td>
<td>5 (A)</td>
<td>14 (B)</td>
<td>19 (E)</td>
</tr>
<tr>
<td>Controls</td>
<td>12 (C)</td>
<td>5 (D)</td>
<td>17 (F)</td>
</tr>
<tr>
<td>Total</td>
<td>17 (G)</td>
<td>19 (H)</td>
<td>36</td>
</tr>
</tbody>
</table>

The relative risk is also known as the risk ratio, and represents the ratio of risk in the exposed group (Cases) to the risk in the unexposed group (Controls). In Table 1, the relative risk of Outcome One is $\frac{(A/E)}{(C/F)}$ or $\frac{(5/19)}{(12/17)} = 0.37$. This result means that the relative risk of Outcome One is 17% less in the exposed group to the controls, or in other words, the exposure is protective (if Outcome One is beneficial). This is usually easier to understand than an odds ratio; when the latest health scare is reported by the media (butter makes you 17% more fat!) they are usually referring to the relative risk. Results of cohort studies are most often quoted as relative risks.

The odds ratio is the ratio of odds of an outcome in the exposed group to the odds of an outcome in the unexposed group. In Table 1, the odds ratio is $\frac{(A/B)}{(C/D)}$ or $\frac{(5/14)}{(12/5)} = 0.14$. Odds ratios are most often provided when reporting the results of case-control studies where the prevalence of the underlying outcome cannot be estimated. Odds ratios are slightly more difficult to understand, unless you get a kick out of maths (so why are you doing medicine?). Think of odds ratios as the odds of a greyhound winning a race (Santa’s little helper at 5/1) and you’ve got the idea. So even though odds ratio and relative risk are often seen as being synonymous, they actually represent completely different values. (It’s only when outcomes are rare that the OR and RR will be similar).

This article is really an introduction to the basics of relevant statistical tests. We have tried to show in the differences between commonly used tests and terms. Most importantly, we hope that this short tutorial helps as you tackle and critically appraise the statistics section of the next paper you read.

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Further reading
5. BMJ “Statistics Notes” or “Statistics for the non-statistician”

What is the Difference Between Sensitivity and Specificity? Or Positive Predictive Value and Negative Predictive Value? And What’s a ROC if It’s Not a Type of Bird?

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Let’s start honestly: sensitivity and specificity are two terms that confuse nearly everyone. As a medical student, they are something that you learn for an exam and then forget, until you meet them again at a journal club and the consultant starts talking about the sensitivity of the test and you frantically try to remind yourself where the false positives went and are the denominator false negatives or positives. Worse yet, when you are the consultant and are faced with a group of bright eyed trainees who