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Importance of Assumptions in Using Statistical Techniques

1.1 Introduction

All researches are conducted under certain assumptions. Validity and accuracy of findings depends upon whether we have fulfilled all the assumptions of data and statistical techniques used in the analysis. For instance, in drawing a sample, simple random sampling requires the population to be homogeneous while stratified sampling assumes it to be heterogeneous. In any research, certain research questions are framed that we try to answer by conducting the study. In solving these questions, we frame hypotheses that are tested with the help of the data generated in the study. These hypotheses are tested using some statistical tests, but these tests depend upon whether the data is nonmetric or metric. Different statistical tests are used for nonmetric and metric data for answering same research questions. More specifically, we use nonparametric tests for nonmetric data and parametric tests for metric data. Thus, it is essential for the researchers to understand the type of data generated in their studies. Parametric tests no doubt provide more accurate findings than the nonparametric tests, but they are based upon one common assumption of normality besides some specific assumptions associated with each test. If normality assumption is severely violated, the parametric tests may distort the findings. Thus, in research studies, assumptions are focused on two spheres: data and statistical tests besides methodological issues. Nowadays, many statistical packages such as IBM SPSS® Statistics software ("SPSS"),[1] Minitab, Statistica, and Statistical Analysis System (SAS) are available for analyzing both nonmetric and metric data, but they do not check the assumptions automatically. However, these software do provide outputs for testing associated assumptions with the statistical tests. We shall now discuss different types of data that can be generated in research studies. By knowing this, one can decide the relevant strategy for answering their research questions.

1 SPSS Inc. was acquired by IBM in October 2009.

Testing Statistical Assumptions in Research, First Edition. J. P. Verma and Abdel-Salam G. Abdel-Salam.

Companion Website: www.wiley.com/go/Verma/Testing_Statistical_Assumptions_Research

1.2 Data Types

Data are classified into two categories: nonmetric and metric. Nonmetric data are also termed as qualitative and metric as quantitative. Nonmetric data are further classified as nominal and ordinal. Nonmetric data are a categorical measurement and are expressed by means of a natural language description. It is often known as "categorical" data. The data such as Student's Specialization = "Economics", Response = "Agree", Gender = "Male", etc. are examples of nonmetric data. These data can be measured on two different scales, i.e. nominal and ordinal.

1.2.1 Nonmetric Data

Nominal data are obtained by categorizing an individual or object into two or more categories, but these categories are not graded. For example, an individual can be classified into male or female category, but we cannot say whether male is higher or female is higher based on the frequency of the data set. Another example of nominal data is the color of the eye. One can be classified into blue, black, or brown eye categories. With this type of data, one can only compute percentage and proportion to know the characteristics of the data. Furthermore, mode is an appropriate measure of central tendency for such a data.

On the other hand, in the ordinal data, categories are graded. The order of items is often defined by assigning numbers to them to show their relative position. Here also, we classify a person, response, or object into one of the many categories, but we can rank them in some order. For example, variables that assess performance (excellent, very good, good, etc.) are ordinal variables. Similarly, attitude (agree, can't say, disagree) and nature (very good, good, bad, etc.) are also ordinal variables. On the basis of the order of an ordinal variable, one may not be sure as to which value is the best or worst on the measured phenomenon. Moreover, the distance between ordered categories is also not measurable. No mathematical operation can be done in the ordinal data. Median and quartile deviation are the appropriate measures of central tendency and variability, respectively, in such data.

1.2.2 Metric Data

Metric data are always associated with a scale measure, and therefore, it is also known as scale data. Such type of data are obtained by measuring some phenomena. Metric data can be measured on two different types of scale, i.e. *interval* and *ratio*. The data measured on interval and ratio scales are also termed as interval data and ratio data, respectively. Interval data are obtained by measuring a phenomenon along a scale where each position is equidistant from one another. In this scale, the distance between the two pairs are equivalent in some way. The only problem with this scale is that the doubling principle breaks down as there is no real zero on the scale. For instance, the eight marks given to an individual on the basis of his or her creativity do not explain that his or her creativity is twice as good as the person with four marks on a 10-point scale. Thus, variables measured on an interval scale have values in which differences are uniform and meaningful but ratios are not. Interval data may be obtained if the parameters such as motivation or level of adjustment is rated on a scale of 1–10.

The data measured on ratio scale has a meaningful zero and has an equidistant measure (i.e. the difference between 30 and 40 is the same as the difference between 60 and 70). Because zero exists in ratio data, 80 marks obtained by person A on a skill test may be considered twice the 40 marks obtained by another person B on the same test. In other words, doubling principle holds in ratio data. All types of mathematical operations can be performed with such kind of data. Examples of ratio data are weight, height, distance, salary, etc.

1.3 Assumptions About Type of Data

We know that for metric data, the parametric statistics are calculated while for nonmetric the nonparametric statistics are used. If we violate these assumptions, the findings may be misleading. We shall show this by means of an example. Before that let us elaborate data assumptions little more. If the data are nominal, we find mode as a suitable measure of central tendency, and if the data are ordinal, we compute median. Since both nominal and ordinal data are nonmetric, we use nonparametric statistics (mode and median). On the other hand, if the data are metric (interval/ratio), we should use parametric statistics such as mean and standard deviation. But we can calculate parametric statistics for the metric data only when the assumption of normality holds. In case the normality violates, we should use nonparametric statistics like median and quartile deviation. Assumptions of data in using measures of central tendency are summarized in Table 1.1.

Let us see what happens if we violate the assumption for the metric data. Consider the marks obtained by the students in an examination as shown in Table 1.2. This is a metric data; hence, without bothering about the normality assumption, let us compute the parametric statistic, mean. Here, the mean of the data set is 46. Can we say that the class average is 46 and report this finding in our research report? Certainly not, as most of the data are less than 46.

Let us see why this situation has arisen. If we look at the distribution of the data, it is skewed toward the positive side of the distribution as shown in Figure 1.1. Since the distribution of data is positively skewed, we can conclude that the normality assumption has been severely violated.

Table 1.1 Assumptions about data in computing measures of central tendency.

Data type	Nature of variable	Appropriate measure of central tendency
Nonmetric	Nominal data	Mode
	Ordinal data	Median
Metric	Interval/ratio (if symmetrical or nearly symmetrical)	Mean
	Interval/ratio (if skewed)	Median

Table 1.2 Marks for the students in an examination.

Student	1	2	3	4	5	6	7	8	9	10
Marks	35	40	30	32	35	39	33	32	91	93

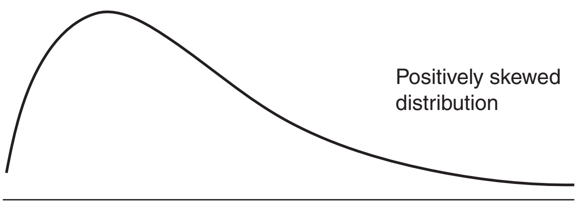

Figure 1.1 Showing the distribution of data.

In a situation where the normality assumption is violated, we can very well use the nonparametric statistic such as median, as shown in Table 1.1. The median of this data set is 35, which can rightly be claimed as an average as most of the scores are around 35 in comparison to 46. Thus, if the data are skewed, then one should report median and quartile deviation as the measures of central tendency and variability, respectively, instead of mean and standard deviation in their project report.

1.4 Statistical Decisions in Hypothesis Testing Experiments

In hypotheses testing experiments, since population parameter is tested for some of its characteristics on the basis of the sample obtained from the population of interest, some errors are bound to happen. These errors are known as statistical errors. We shall investigate these errors and their repercussion in detail in the following sections.

1.4.1 Type I and Type II Errors

In hypotheses testing experiments, research hypothesis is tested by negating the null hypothesis. The focus of the researcher is to test whether the null hypothesis can be rejected on the basis of the given sampled data. The readers should note that a null hypothesis is never accepted. Either it is rejected or we fail to reject it on the basis of the given data. In hypothesis testing experiments, we test population characteristics on the basis of the sample; hence, some errors are bound to happen. Let us see what these errors are all about. While testing the null hypothesis, four types of decisions are possible, out of which two are correct and two are wrong. The two wrong decisions are rejecting the null hypothesis when it is true and failing to reject the null hypothesis when it is false. On the other hand, there are two correct decisions: rejecting the null hypothesis when it is not correct and not rejecting the null hypothesis when it is true. All these decisions have been summarized in Table 1.3.

The two wrong decisions discussed above are referred to as statistical errors. Rejecting a null hypothesis when it is true is known as "Type I error (α)" and failing to reject the null hypothesis when it is false is "Type II error (β)." Type I error is known as false positive because this error facilitates the researcher to accept the false claim. Similarly, Type II error is also known as false negative because this error guides the researcher not to accept the correct claim in the experiment. Since both the errors result in erroneous conclusion, the researcher always tries to minimize them. But the simultaneous minimization of both these errors, α and β, are not possible for a fixed sample size because if α decreases, then β increases and vice versa. If we wish to decrease these two errors simultaneously, sample size needs to be increased. But if the sample size cannot be increased, then one should fix the most severe error to an acceptable low level in the experiment. Out of the two errors, Type I error is more severe than Type II error. It is because Type I error forces the researcher to reject the correct null hypothesis and accept the false claim in the experiment. On the other hand, Type II error dictates the researcher not to accept the correct claim by not rejecting the null hypothesis. Since accepting the wrong claim

Table 1.3 Statistical errors in hypothesis testing experiment.

		Actual state	
		H_0 true	**H_0 false**
Researcher's decision	Reject H_0	Type I error (α) (false positive)	Correct decision ($1 - \beta$)
	Do not reject H_0	Correct decision	Type II error (β) (false negative)

Table 1.4 Implication of errors in hypothesis testing experiment.

		Actual state	
		H_0 true	**H_0 false**
Researcher's decision	Reject H_0	Type I error (α) (wrongly concluding that drug is effective)	Correct decision ($1-\beta$)
	Do not reject H_0	Correct decision	Type II error (β) (wrongly rejecting the effective drug)

(α) is more serious than not accepting the correct claim (β), α is kept at low level in comparison to β.

Let us consider an experiment to test the effectiveness of a drug. Here, the null hypothesis H_0 is that the drug is not effective, which is tested against the alternative hypothesis H_1 that the drug is effective. In committing Type I error, the researcher will wrongly reject the null hypothesis H_0 and will accept the wrong claim about the drug to be effective. In other words, wrongly rejecting the null hypothesis will guide the researcher to accept the wrong claim that may be serious in nature.

On the other hand, if Type II error is committed, the researcher does not reject the null hypothesis and the correct claim about the effectiveness of the drug is rejected. Implications of these errors have been shown in Table 1.4.

Type I error can also be considered as consumer's risk and Type II error as producer's risk. For the researcher, consumer's risk is more serious than the producer's risk; hence, these two errors must be decided in advance in the experiment.

Probability of committing Type I error is known as level of significance and is denoted by α. Similarly probability of Type II error is represented by β. Thus, we can write:

- α = Prob. (Rejecting the null hypothesis when H_0 is true)
- β = Prob. (Not rejecting the null hypothesis when H_1 is true)

Generally, Type I error (α) is taken as 0.05 or 0.01, whereas Type II error (β) is kept at 0.2 or less in the study. Since choice of α depends upon the severity of accepting the wrong claim, it may be selected even lesser than 0.01 depending upon the situation.

1.4.2 Understanding Power of Test

Power of a test is the probability of rejecting the null hypothesis when the research hypothesis is true. In other words, it is the probability of rejecting null hypothesis correctly. The power of a test is computed by $1-\beta$. If power is fixed at 0.8 in the drug testing experiment, it simply indicates that the probability of correctly rejecting the null hypothesis is 0.80. In other words, if the null hypothesis is rejected 80% of the time, the claim about the drug would be true. In estimating the sample size in the experiment, one needs to decide in advance as to how much power one wishes to have in the experiment. Logically, one should fix a power of at least 0.8 in the experiment. This indicates that 80% of the trials should reject the null hypothesis correctly. If power of the test is kept at 50% or less, then there is no meaning in performing the test. Simply toss a coin and decide whether the drug is effective or not.

1.4.3 Relationship Between Type I and Type II Errors

We know that Type I and Type II errors are related to each other. If one error decreases, another increases. Let us see how change in Type I error affects Type II error. We shall discuss this relationship with the help of an example. Let us suppose that the weight x is normally distributed with unknown mean μ and standard deviation 2 kg. For testing the hypothesis $H_0 : \mu = 60$ against $H_1 : \mu > 60$ at 5% level with 40 samples, let us see what would be the power in the test. We know that under the null hypothesis, sample mean follows normal distribution. To find the distribution of $\bar{x}$ under H_1, the populations mean needs to be specified. Let us assume that we wish to test the above-mentioned null hypothesis $H_0 : \mu = 60$ against the alternative hypothesis $H_1 : \mu = 64$. Then under H_0 and H_1, the distribution of $\bar{x}$ shall be as shown in Figure 1.2.

Here, α is the probability of rejecting H_0 when it is true. The null hypothesis H_0 is rejected if the test statistic falls in the rejection region as shown by the dotted area in Figure 1.2. On the other hand, β is the probability of not rejecting H_0 when H_1 is true and this area is denoted by the shaded lines. The power $(1-\beta)$ is the remaining area of the normal distribution when H_1 is true. You can see from Figure 1.2 that if α decreases, then β increases, and as a result, the power decreases. It can be noticed from the figure that the amount of decrease in α is not equal to the amount of increase in β. It is interesting to note that on decreasing the probability of Type I error (α), power of the test $(1-\beta)$ also decreases and vice versa.

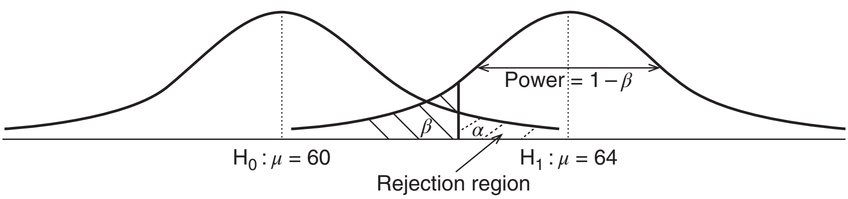

Figure 1.2 Distribution of mean under null and alternative hypotheses.

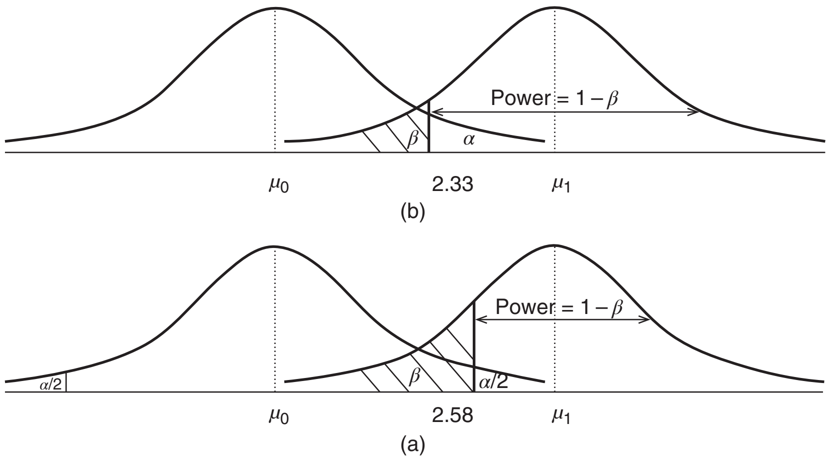

Figure 1.3 Showing comparison of power in (b) one- and (a) two-tailed tests at 1% level.

Often researchers feel elated if their null hypothesis is rejected at a significance level of 0.01 instead of 0.05 because they feel that their results are more powerful. If that is the case, why not reduce α to zero. In that case, the null hypothesis will never be rejected whatsoever the claim may be. On the other hand, if β is taken as 0, then every time null hypothesis would be rejected in favor of the claim. Thus, the researcher should choose α and β judiciously in the study.

1.4.4 One-Tailed and Two-Tailed Tests

In determining the sample size in hypothesis testing experiments, one needs to decide the type of test (one-tailed or two-tailed) to be used in the study. In a one-tailed test, the entire critical region, α, lies in one tail, whereas in a two-tailed test, it is divided to both the tails. Due to this reason, in a one-tailed test, β becomes less in comparison to that of a two-tailed test for the same α; this enhances power $(1 - \beta)$ in the one-tailed test. Thus, the power in the experiment can be increased at the cost of increasing α. The relationship between α and power $(1 - \beta)$ can be seen graphically in Figure 1.3. We may conclude that a one-tailed test is more powerful than a two-tailed test for the same level of α.

1.5 Sample Size in Research Studies

Findings of any research are based on the assumption that the appropriate number of sample elements has been selected in the study. The researchers are always in dilemma as to how much sample is enough for the study. A small sample provides inaccurate findings, whereas a large sample is an unnecessary use of extra resources like time and money. A small sample may not detect the effect in the experiment, whereas in a large sample, even a small effect may be significant, which may not have any practical utility. Criteria for choosing appropriate sample size depend upon whether the sample is being selected for the survey studies or for the hypotheses testing experiments. In survey studies, the sample size is determined on the basis of the amount of precision required in estimating a population parameter. On the other hand, in hypotheses testing experiments, it is estimated on the basis of the power required in the experiment. Details on sample size determination using software in research studies can be seen in the book titled *Determination of Sample Size and Power Analysis using G*Power Software* (Verma 2017).

To determine the sample size in survey studies, we need to know the population variability, amount of precision, and confidence coefficient required in estimating the population parameter. The following formula can be used to estimate the sample size:

$$n = Z^2_{\alpha/2} \frac{pq}{d^2}$$

where p is the population proportion of the characteristics, generally estimated from similar studies conducted earlier, $q = 1 - p$, $Z_{\alpha/2}$ is the z value at a significance level α for a two-tailed test, and d is the precision required. Since p is rarely known, let us take p as 0.5 (assume maximum variance), and if we assume $Z_{\alpha/2}$ as approximately 2 (z value at 5% level), then sample size for different level of precisions at 5% level can be computed using the formula as shown in Table 1.5.

In a hypothesis testing experiment, a researcher often decides α and takes some sample data for testing his or her hypothesis on some population parameter. If the null hypothesis is rejected at say 5% level, then the conclusion is drawn that the treatment is effective. But the question is: How effective is

Table 1.5 Sample size for different precision.

Precision percentage	Precision level (d)	Sample size
10	0.1	100
5	0.05	400
4	0.04	625
3	0.03	1111
2	0.02	2500
1	0.01	10 000

the treatment? Simply by rejecting the null hypothesis, can we conclude that the treatment is effective in 95% trials if the same experiment is conducted 100 times? Here comes the role of defining power in the experiment. If the power is fixed at 0.9 in the experiment and the sample size is determined accordingly, then we can be sure that the null hypothesis will be correctly rejected 90% of the time.

Thus, for the researchers, two things are very important to fix in the hypothesis testing experiment: minimum effect that one wishes to test in the experiment and the power of the test besides Type I error at some predefined level. The whole discussion can be illustrated with an example from weight control research.

A health management company approached a big organization to sell its four-week weight management workshop to its obese employees. The company claims that its workshop will facilitate the employees to reduce their weight and improve functional efficiency. The CEO advised the company to conduct a research to see the effectiveness of the workshop on few employees, and if the findings of the workshop were encouraging, then he will allow the employees to join the workshop on a subsidized rate. During the experiment, the weight of the 15 participants were taken before and after the workshop. The null hypothesis in the experiment was that there will not be any change in the average weights of the participants against the research hypothesis that the post-workshop average weight will reduce significantly in comparison to the pre-workshop average weight. The null hypothesis was tested at 5% level. After analyzing the pre-post data on weight, the null hypothesis was rejected at 5% level. The company claimed that their workshop was effective at 5% level. In other words, 95% of the subjects reduced their weights. With this finding, should the CEO allow the company to launch the workshop for its employees? Several questions may be raised on the findings. First of all, how much weight reduction actually happened, and if 95% of the employees reduced their weights say only 150 g in four weeks, will the workshop be worth attending? Second question is: How much was the average weight of the subjects who participated in the workshop because a person weighing 100 kg will reduce faster than the person weighing 75 kg. The third question is: What was the power in the experiment? If the power of the test is only 0.5, then the rejection of the null hypothesis is not a guarantee of effectiveness of the program. In order to make the findings reliable, the researcher should have fixed the minimum detectable difference in post- and pre-workshop weight say 2 kg, the power say 0.9, and then the sample size required to detect 2-kg weight reduction should have been estimated. By freezing these conditions, if the null hypothesis would have been rejected in the experiment conducted on the estimated sample size, then one can say that the workshop will reduce the weight of the participants at least 2 kg in four-week time in 90% of the trials.

In hypothesis testing experiments, sample size is determined using the following information:

1) Minimum detectable difference (d)
2) Power in the test ($1-\beta$)
3) Population variance (σ^2)
4) Type I error (α)
5) Type of the test (one-tailed or two-tailed)

While planning a hypothesis testing experiment, the researcher needs to decide and freeze the above-mentioned parameters to find the required sample size in the experiment. Using the following formula, the sample size can be computed. The meanings of the symbols are as usual:

$$n = \frac{\sigma^2}{d^2}(Z_\alpha + Z_\beta)^2$$

1.6 Effect of Violating Assumptions

In survey studies, we are mainly concerned with the precision and confidence coefficient in estimating population characteristics. Hence, violation of assumptions in such studies affects these two benchmarks. For instance, in case of extreme violation of normality assumption, the precision in estimating population parameter may not be same as claimed or the confidence coefficient in interval estimates may not be in conformity with what has been stated in the findings. Similarly, if the data is nonmetric and we apply parametric statistics for estimating population characteristics, the results will be completely absurd. Some of the assumptions may not be very serious but the others may affect the findings adversely. In case of extreme violation of certain assumptions, the results may be completely misleading. Thus, it is important for the researchers to investigate each and every assumption associated with the data and statistical techniques used in the survey studies carefully.

In hypothesis testing experiments, violation of assumptions for the data and statistical tests associated with the analysis affects three benchmarks: Type I error, power, and effect size. Depending upon the kind of violation of assumptions, these crucial factors get affected individually. The researcher may report the findings that the research hypothesis may be accepted at 5% significance level, but violation of assumption may actually raise the level to 10%. Similarly, if the study reports the power as 0.8, due to violation of assumption, it may actually be 0.6. Another disadvantage for not checking the assumptions may affect the claim on the effect size. In the weight control example discussed above, if the researcher claims that the minimum reduction of weight would be 2 kg if somebody participated in the workshop, this claim may be refuted in case of violation of the associated assumptions in the study.

What the researchers should do to avoid the pitfalls in reporting the findings? First, one should check the data type and choose the statistical analysis accordingly. If the data is metric, then one must check the normality assumption before using any parametric test. Second, one should investigate as to what are the associated assumptions of the selected statistical technique and check them accordingly.

Exercises

Multiple-Choice Questions

Note: Choose the most appropriate answer for each question.

1. Which of the following is affected by all the scores in a distribution?
   a. Mean
   b. Median
   c. Mode
   d. None of the above

2. If student's behavior has to be assessed by a panel of five judges, which of the following measures would be appropriate?
   a. Mean
   b. Median
   c. Mode
   d. None of the above

3. Which measures of central tendency will be suitable to compare height of the students in two classes?
   a. Mode
   b. Mean
   c. Median
   d. None

4. Which measure would be suitable to compare sale of different brands of mobile phones?
   a. Mean
   b. Median
   c. Mode
   d. Any of the above

5. Nominal data refers to the
a. Metric data
b. Continuous data
c. Dichotomous data
d. Integer data

6. Which of the following statement is not correct?
a. Nominal data is also known as categorical data.
b. In interval data, there is no real zero.
c. In ratio data, the doubling principle holds.
d. In ratio data, a person having scored 60 in a test may not be considered to be twice better than the one having scored 30.

7. Which of the following statement is correct?
a. The mean can be computed for the nominal data.
b. The mean is affected by the change of origin and scale.
c. Mean can be computed for the ordinal data.
d. Mean can be computed from truncated class interval.

8. Which of the following statement is not correct?
a. The mean should not be calculated as a measure of central tendency if there are outliers in the data set.
b. Median is not affected by the extreme scores.
c. In skewed data, median is the best measure of central tendency.
d. Outliers affect the mode.

9. Proportion and percentage statistics are best suited for which type of scores?
a. Nominal
b. Ordinal
c. Interval
d. Ratio

10. If there are no objective criteria of assessment, then the characteristics should be measured on which type of scale?
a. Interval
b. Ordinal
c. Ratio
d. Nominal

11. The Type I error can be best described by which of the following probability?
a. P (Rejecting H_0/H_0 is true)
b. P (Rejecting H_0/H_1 is true)
c. P (Rejecting H_0/H_0 is false)
d. P (Rejecting H_0/H_1 is false)

12. Which of the following probability defines Type II error correctly?
a. P (Not rejecting H_0/H_1 is false)
b. P (Not rejecting H_1/H_0 is false)
c. P (Not rejecting H_0/H_1 is true)
d. P (Not rejecting H_1/H_0 is true)

13. If the Type II error is represented by β, then power of the test is computed by
a. $1 + \beta$
b. $1 - \beta$
c. $\beta - 1$
d. β

14. The relationship between α and β can be best explained by
a. $\alpha = \beta$
b. $\alpha > \beta$
c. $\alpha < \beta$
d. $\alpha = k/\beta$

15. Choose the correct statement in relation to a research study.
a. Type I and Type II errors are equally severe.
b. Type I error is more severe than Type II error.
c. Type II error is more severe than Type I error.
d. Both the errors are not so severe.

16. The term $(1 - \alpha)$ can be defined as
a. The probability of a Type I error
b. The power of a test
c. The probability of a Type II error
d. The probability of not rejecting the null hypothesis when it is true

17. If a null hypothesis is not rejected at 5% level, what conclusion can be drawn?
a. The null hypothesis will be rejected at 1% level of significance.
b. The null hypothesis will be rejected at 10% level.
c. The null hypothesis will not be rejected at 1% level.
d. No conclusion could be drawn.

18. If the null hypothesis is rejected at 0.01 significance level, then
   a. It will also be rejected at the 0.05 significance level.
   b. It will not be rejected at the 0.05 significance level.
   c. It may not be rejected at the 0.05 significance level.
   d. It may not be rejected at the 0.02 significance level.

19. Other things being equal, which of the following actions will reduce the power in a hypothesis testing experiment?
   I. Increasing sample size
   II. Increasing significance level
   III. Increasing Type II error
   a. I only
   b. II only
   c. III only
   d. All of the above

20. Which of the following statement is not correct?
   a. Larger sample is required if Type I error decreases provided other conditions are same.
   b. Larger sample is required if Type II error increases provided other conditions are same.
   c. Sample size is directly proportional to the variability of the population.
   d. Sample size is inversely proportional to the effect size.

Short-Answer Questions

1. How many types of data exist in research? Explain them with examples. What kinds of analyses are possible with each data type?

2. Why Type I error is more serious in nature? Explain with examples.

3. What is the importance of power in hypothesis testing experiment? How can power be enhanced in testing?

4. Can both types of errors be reduced in research, if so how? Should Type I error be kept very low?

5. What are the various considerations in deciding the sample size in survey studies?

6. What are the considerations in deciding the sample size in hypothesis testing experiment?

Answers

Multiple-Choice Questions

1. a
2. b
3. b
4. c
5. c
6. d
7. b
8. d
9. a
10. b
11. a
12. c
13. b
14. d
15. b
16. d
17. c
18. a
19. c
20. b