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Statistical Testing to Provides a Mechanism for Making Quantitative Decisions for Data Analysis

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Abstract: ***A statistical test provides a system for making quantitative decisions for a given data set. This system determines whether there is enough evidence to "reject" a assumption or hypothesis about the process. The assumption is called the null hypothesis. Not rejecting may be a good result if we want to continue to act as if we "believe" the null hypothesis is true. Or it may be a disappointing result, possibly indicating we may not yet have enough data to "prove" something by rejecting the null hypothesis. Statistical tests are used in hypothesis testing. Statistical tests assume a null hypothesis of no relationship or no difference between groups. In this paper we state the null and alternative hypotheses. Compare the computed chi-square statistic with the critical value of chi-square; reject the null hypothesis if the chi-square is equal to or larger than the critical value; accept the null hypothesis if the chi-square is less than the critical value. We used real life data set for experimental.***

Keywords: Hypothesis, Believe, Reject, Critical, Alternative

I. INTRODUCTION

A statistical hypothesis is a confirmatory data analysis technique. Hypothesis that is testable based on observing a process that is modeled via a set of random variables. A statistical hypothesis test is called method of statistical inference. Statistical data sets are or data set obtained by sampling is compared against a synthetic data set. An alternative hypothesis is proposed for the statistical-relationship between the two datasets. It is compared to an idealized null hypothesis. This hypothesis tells that no relationship between these two datasets. The comparison is statistically significant and relationship between the datasets would be according to a threshold probability and the level of significance. Hypothesis tests are useful for determining outcomes of a study, lead to a rejection of the null hypothesis. Hypothesis testing is used with experimental data to make decisions. It determines whether an experiment performed offers sufficient evidence to reject a proposal[1,2].

Null hypothesis is the he basic assumption of a statistical test and can quantify and interpret statistical measurements to determine null hypothesis can be accepted or not. A Null Hypothesis implies that there is no strong difference in a given set of observations. To define a statement on whether to reject the null hypothesis a test statistic will be determined. The decision is taken based on the test statistical quantitative value[12].

Assumption and Postulate

The terms assumption, postulate occur most frequently in hypothesis but are often confused. Hence these terms need clear explanation [8,9,10].

Assumption: Assumption takes things for granted so that the situation is simplified for procedure. Assumptions merely facilitate the progress of an agreement for partial simplification and introducing restrictive conditions. Assumption means restrictive conditions before the argument can become valid. Assumptions are made on the basis of logical insight and their faithfulness can be observed on the basis of data or evidences. The postulates are the basis and form the original point of an argument. Assumptions are a matter of choice

Postulate: Postulates are beliefs of most scientific activity. A postulate is a statement assumed to be true without need of proof. A postulate states an assumption and made some relationship between objects. By logical deductions we can derive statements. From postulates we are entirely within the ideas. There is no point for experimental proof of deductions. Such a request would be meaningless. The only appeal for proof that is appropriate is entirely within the realm of logic

A good hypothesis must have following characteristics [2,5]

- It is not formulated in the form of a question.
- It can be empirically testable, whether it is right or wrong.
- It needs to be specific and precise.
- It should not be contradictory.

- It should specify relationship between variables which is to be established.
- It describes only one issue. A hypothesis formed either in descriptive or relational form.
- It guarantees that available tools and techniques will be effectively used verification.

Hypothesis should be conceptually clear: The concepts used in the hypothesis should be clearly defined, not only formally but also operationally.

II. LITERATURE SURVEY

In 2015 Kim, Jae et al proposed **"Choose the Level of Significance: A Pedagogical Note".** They present discussion with several examples for students, along with the selected references to the past and recent academic research. While the conventional levels may still serve as useful benchmarks, mindless and mechanical choice of these levels should be avoided. Students of basic statistics should understand that the level of significance should be chosen with relevant contexts in mind, in careful consideration of the key factors such as sample size and expected losses[2].

In 2016 Marko A. Hofmann et al proposed **"Null Hypothesis Significance Testing In Simulation"**. They have argued that focusing on p-values is not conducive to science, and that NHST is often dangerously misunderstood. A critical reflection of the arguments contra NHST shows, however, that although NHST is indeed ill-suited for many simulation applications and objectives it is by no means superfluous, neither in general, nor in particular for simulation. With special respect to simulation two strong conclusions can be drawn: 1. p-values are ill-suited for all exploratory simulation for three reasons, a researcher can achieve statistical significance by increasing effect size or sample size (Test statistic significance size of effect sample size;. Since increasing sample size in an exploratory setting is trivial only the effect size can be of any interest. Second, exact p-values create an illusion of precision which is seldom, if at all, justified in exploratory simulation [3].

In 2017 Sendil Mourougan et al proposed **"Hypothesis Development and Testing".** They discuss the methods of working up a good hypothesis and statistical concepts of hypothesis testing. The empirical approach to research cannot eliminate uncertainty completely. At the best, it can quantify uncertainty. This uncertainty can be of 2 types: Type I error (falsely rejecting a null hypothesis) and type II error (falsely accepting a null hypothesis). The acceptable magnitudes of type I and type II errors are set in advance and are important for sample size calculations. They reject the null hypothesis and by default accept the alternative hypothesis. If we fail to reject the null hypothesis, they accept it by default. They looked at the concept of hypothesis followed by the types of hypothesis and way to validate hypothesis to make an informed decision[4].

In 2018 Daniel Goldman proposed **"The Basics of Hypothesis Tests and Their Interpretations".** They summarize the nature of hypothesis tests, as well as their interpretations, including the importance of understanding the underlying phenomenon being tested. They assume that our null hypothesis is true. Then make a number of observations, and estimate the probability of seeing those observations, under the assumption that our null hypothesis is true. They also assume that observations we make are not unusual: if they observe something, assume that it is not an extremely rare observation. Admittedly, the example that provided was pathological. They are generated through our understanding of real world phenomenon. It is because of our understanding of how height varies through a population that assumes normality and other conditions necessary to perform our hypothesis test [5].

In 2019 Jae H. Kim et al proposed **"Interval-Based Hypothesis Testing and Its Applications to Economics and Finance".** They presents a brief review of interval-based hypothesis testing, widely used in bio-statistics, medical science, and psychology, namely, tests for minimum-effect, equivalence, and non-inferiority. They present the methods in the contexts of a one-sample t-test and a test for linear restrictions in a regression. They present applications in testing for market efficiency, validity of asset-pricing models, and persistence of economic time series. They argue that, from the point of view of economics and finance, interval-based hypothesis testing provides more sensible inferential outcomes than those based on point-null hypothesis [6].

In 2020 Jingyi Jessica e al proposed **"Statistical Hypothesis Testing versus Machine Learning Binary Classification: Distinctions and Guidelines".** They disentangle the puzzle for data science students and researchers by offering practical guidelines for choosing between the two strategies. Making binary decisions is a common data analytical task in scientific research and industrial applications. They summarize key distinctions between these two strategies in three aspects and list five practical guidelines for data analysts to choose the appropriate strategy for specific analysis needs. They demonstrate the use of those guidelines in a cancer driver gene prediction example[8].

In 2020 David Delgado-Gómez et al proposed **"Improving the Teaching of Hypothesis Testing Using a Divide-and-Conquer Strategy and Content Exposure Control".** They proposed strategy is designed to sequentially explain and evaluate the different concepts involved in hypothesis testing, ensuring that a new concept is not presented until the previous one has been fully assimilated. The usefulness of the proposed approach was assessed in an experiment in which 89 first-year students enrolled in the Statistics course within the Industrial Engineering degree participated. Based on the results of a test aimed at evaluating the acquired knowledge, it was observed that students who used the developed application based on the proposed approach obtained statistically significant higher scores than those that attended a traditional class (p-value < 0.001), regardless of whether they used the learning tool before or after the traditional class. They proposed a new approach has been proposed for the teaching of hypothesis testing[10].

In 2020 Dan-Yu Lin et al proposed **"Evaluating the Efficacy of COVID-19 Vaccines".** They demonstrate the advantages of this strategy through realistic simulation studies. They showed how this approach can provide rigorous interim monitoring of the trials and efficient assessment of the durability of vaccine efficacy. They presented a simple and rigorous framework to consider the totality of evidence when evaluating the benefit of a COVID-19 vaccine in reducing SARS-CoV-2 infection, COVID- 19, and severe COVID-19. The proposed methods are more robust to different scenarios of vaccine efficacy than the use of a single primary endpoint. They recommend using the combined test to provide an overall assessment of worthwhile vaccine efficacy, then using the sequential test to determine the endpoints against which the vaccine is efficacious [12].

III. PROPOSED APPROACH

The process of hypothesis testing consists of four main steps

Step 1: During this stage we formulate two hypotheses to test:

Null hypothesis (Ho): A hypothesis that proposes observations there is no effect relationship or difference between two or more groups.

Alternative hypothesis (Ha): A hypothesis that proposes observations are influenced by some non-random

Step 2: The significance level (α) is the probability threshold that determines when rejects the null hypothesis. We can choose a significant level of 0.01, 0.05, or 0.10, but any value between 0 and 1.

Step 3: Given a test statistic, assess the probabilities associated with the test statistic which is called a p-value. P-value is the probability that a test statistic at least as significant as the one observed.

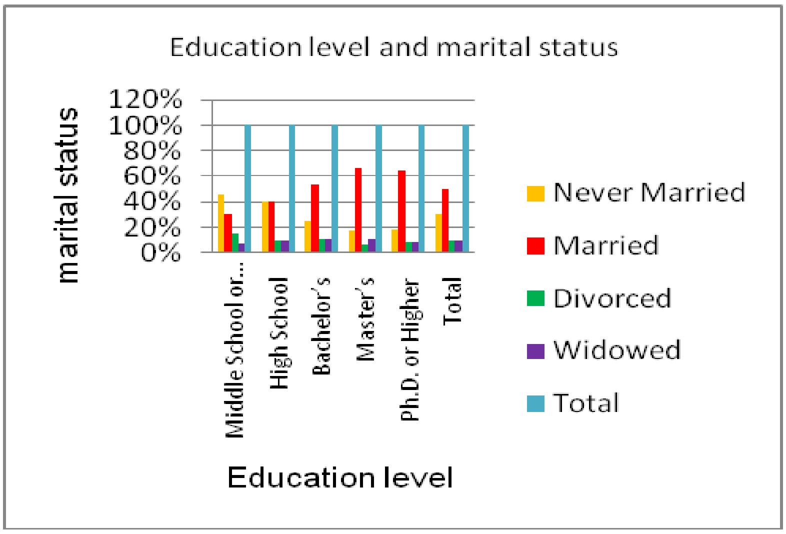
Step 4: Compare the calculated p-value with the given level of significance α. if the p-value is less than or equal to α, reject the null hypothesis and if it is greater than α, we fail to reject the null hypothesis.

Step 5: When we decide to reject or fail to reject the null hypothesis, two types of errors might occur.

Type I error: A Type I error occurs when we reject a null hypothesis when it is

IV. EXPERIMENTAL ANALYSIS

For the experimental analysis we took 300 records as a random sample from 1000 record data. The numbers in this table are known as the observed frequencies. There is 4 marital status categories and 5 education levels. We succeeded in collecting data on our entire sample of n = 300 respondents. We have 84 respondents with a Bachelor's degree. We have 30 divorced respondents. We have 9 divorced respondents with a Bachelor's degree. Now, marital status and education are related -thus not independent- in our sample. Figure 2 show comparison the graph. Which can also proved with the help Chi-Square.



$$\chi^2_{calculated} > \chi^2_{tabular}$$

So we reject Null Hypothesis (Ho) and accept alternate Hypothesis

Alternative hypothesis (Ha): There is significant relation between the marital status and education level

CONCLUSION

There are several methods exist for performing statistical test but these method are dependent upon the type of data and variables. In the proposed work chi-square independence test used for testing if two categorical variables are related in some population. In this paper we state the null and alternative hypotheses. Compare the computed chi-square statistic with the critical value of chi-square; reject the null hypothesis if the chi-square is equal to or larger than the critical value; accept the null hypothesis if the chi-square is less than the critical value. We used real life data set for experimental.

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