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Review Article

"Understanding Discrete Statistical Distributions: A Medical Research Perspective"

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I N F O

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E D I T O R I A L

Background: Statistical distributions play a critical role in medical sciences by providing the mathematical foundation for analysing and interpreting biomedical data. From clinical trials to epidemiological research, their appropriate application enables informed decision-making,trend identification, and evaluation of treatment efficacy. Distributions such as Normal (via the Central Limit Theorem), Binomial, Poisson, Exponential, and Weibull are widely used for modelling continuous data, binary outcomes, rare events, and time-to-event data, respectively.

Aims/Objectives: To explore the theoretical framework and practical utility of key statistical distributions—particularly discrete distributions—in medical research, and to demonstrate their applications using real-world numerical examples.

Methods: A descriptive analytical approach was adopted, integrating theoretical concepts with mathematical formulations. Applications were illustrated through examples from clinical trials, diagnostic testing, epidemiology, and survival analysis.

Results: Quantitative analysis demonstrated the effectiveness of discrete distributions in medical contexts. The Binomial model showed probabilities of 0.2508 (25.08%) for treatment success and 0.323 (32.3%) for diagnostic accuracy. The Poisson distribution yielded probabilities of 0.036 (3.6%) for rare disease incidence and 0.090 (9.0%) for patient arrivals. The Geometric distribution indicated probabilities of 0.0656 (6.56%) for relapse timing, with an expected response time of 3.33 weeks. The hypergeometric distribution produced probabilities of 0.256 (25.6%) in finite population sampling scenarios. The Negative Binomial distribution demonstrated a 0.055 (5.5%) probability of repeated relapses, effectively capturing over dispersion in medical data.

Conclusion: Statistical distributions are essential in medical research, enabling accurate modelling, reliable inference, and evidence-based clinical decision-making.

Keywords: Statistical distributions, probability distributions in medical science, Epidemiological research, Binomial distribution, Poisson distribution, Negative Binomial distribution, Geometric Distribution, hyper geometric distribution.

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Introduction

In modern medical research and clinical practice, the use of statistical distributions has become an indispensable tool for interpreting data, evaluating treatments, and improving patient care. The complexity and variability inherent in biological systems demand rigorous statistical approaches to draw valid and actionable conclusions. As such, statistical distributions form the backbone of data modelling and inference in medical sciences, enabling researchers to describe, understand, and predict the behaviour of health-related variables with precision.

Distributions such as the normal, binomial, Poisson, Weibull, exponential, and log-normal are frequently used in the analysis of medical and pharmaceutical data. These models are essential for tasks such as determining the probability of disease occurrence, modelling survival times, estimating drug efficacy, and quantifying uncertainty in diagnostic procedures.[1,3] For instance, the normal distribution is commonly applied in clinical trials and laboratory studies due to its assumption of symmetry and central tendency in biological data,[10] while the Poisson and negative binomial distributions are well-suited for modeling rare events or count data, such as hospital readmissions or adverse drug reactions. [7]

The practical utility of these distributions extends further into areas such as survival analysis, where Weibull and exponential distributions are instrumental in modelling time-to-event data, particularly in oncology and epidemiology.[5] In pharmaceutical applications, statistical distributions aid in pharmacokinetic modelling, dose-response assessment, and quality control.[3] Moreover, the increasing availability of large-scale biomedical datasets and the integration of data science and predictive analytics into healthcare have amplified the importance of advanced probabilistic models .[5,6]

Despite their wide applicability, challenges persist in selecting appropriate distributions for specific data types and research contexts. Common issues include overdispersion, skewness, censoring, and small sample sizes—all of which can significantly affect inference quality if not properly addressed.[4] Recent research emphasizes the importance of robust distributional testing procedures and model diagnostics to ensure reliability.[9] For example, censored data in survival studies require tailored models and testing strategies, as discussed extensively in foundational statistical literature. [8,9]

Furthermore, the rise of novel modelling paradigms, such as the k-statistics approach in epidemiology,[11] reflects the ongoing innovation in how distributions are adapted to capture emerging patterns in complex systems, including pandemics and chronic disease progression.

This article synthesizes theoretical insights and practical examples of statistical distributions used in medical sciences. We aim to offer a structured exploration of distributional applications—ranging from descriptive statistics to inferential models—and to provide mathematical formulations that highlight both classical and contemporary approaches. Drawing from authoritative sources,[1,7,10] we discuss not only the selection and implementation of distributions but also the interpretive nuances critical to medical decision-making.

By integrating foundational knowledge with real-world examples, we contribute to the growing body of literature aimed at enhancing statistical literacy among medical researchers, clinicians, and students. This work ultimately underscores the indispensable role of statistical distributions in advancing evidence-based medicine and promoting methodological rigor in healthcare analytics.

Binomial Distribution

Theoretical Background

The Binomial distribution describes the probability of obtaining exactly ‘k’ successes in ‘n’ independent Bernoulli trials, where each trial has a probability ‘p’ of success and ‘q’ (q=1−p) of failure.

The probability mass function (PMF) is given by:

$$P(X=k) = \binom{n}{k} p^k (1-p)^{n-k},$$

, where: X = number of successes, n = total number of trials, k = number of successful outcomes, p = probability of success in a single trial, q = probability of failure, and is the binomial coefficient.

Applications Of Binomial Distribution In Medical Sciences

Clinical Trials and Drug Testing

The binomial model helps estimate the probability of treatment success. In a clinical trial, if a new drug has a known success rate, the probability of a specific number of patients benefiting from it can be determined using the binomial distribution.

Diagnostic Test Accuracy

Medical tests have sensitivity (true positive rate) and specificity (true negative rate). The binomial distribution is used to calculate the probability of correctly identifying diseased and non-diseased individuals in a sample.

Patient Survival Analysis

The probability of a patient surviving a certain period after receiving treatment follows a binomial distribution when survival is measured in binary terms (alive or deceased).

Mathematical Examples of Binomial Distribution in Medical Sciences

Example 1: Probability of Drug Effectiveness in a Clinical Trial

A new drug has a 75% success rate in treating a disease. If 10 patients receive the drug, what is the probability that exactly 7 patients recover?

Using the binomial formula: n=10, p=75%=0.75 and

q=1-p=1-0.75=0.25

$$P(X=7) = \binom{10}{7}(0.75)^7(1-0.75)^{10-7} = \frac{10!}{7!*3!}(0.134)(0.015) = 120\times0.134\times0.0156 = 0.2508.$$

So, the probability that exactly 7 patients recover is 25.08%.

Example 2: Probability of Correct Disease Detection Using a Diagnostic Test

A diagnostic test for a disease has an accuracy of 85%. If 20 patients with the disease are tested, what is the probability that at least 18 are correctly diagnosed?

We calculate:

$P(X\geq18) = P(X=18) + P(X=19) + P(X=20)$

Using the binomial formula for each case, n=20, p=85%=0.85 and q=1-p=1-0.85=0.15

$$P(X\geq18) = \binom{20}{18}((0.85)^{18}(0.15)^{20-18} + \binom{20}{19}((0.85)^{19}(0.15)^{20-19} + \binom{20}{20}((0.85)^{20}(0.15)^{20-20}$$

Computing each term and summing the probabilities, we find: $P(X\geq18) \approx 0.323$

So, the probability of correctly diagnosing at least 18 patients is 32.3%.

Example 3: Patient Survival Probability after Surgery

A certain surgery has a 60% survival rate. If 5 patients undergo the surgery, what is the probability that at most 3 survive?

We compute:

$P(X\leq3) = P(X=0) + P(X=1) + P(X=2) + P(X=3)$

Using the binomial formula for each case, n=5, p=60%=0.6 and q=1-p=1-0.6=0.4

$$P(X\leq3) = \binom{5}{0}(0.6)^0(0.4)^{5-0} + \binom{5}{1}(0.6)^1(0.4)^{5-1} + \binom{5}{2}(0.6)^2(0.4)^{5-2} + \binom{5}{3}(0.6)^3(0.4)^{5-3}$$

Summing the probabilities, then get $(X\leq3) \approx 0.663$

So, the probability that at most 3 patients survive is 66.3%.

Poisson Distribution

Theoretical Background of Poisson Distribution

The Poisson distribution is used to model random, rare, and independent events occurring within a fixed interval of time or space. It is particularly relevant in medical sciences for studying the occurrence of diseases, hospital admissions, and service demands.

The Poisson distribution is defined as:

$P(X=k) = (e^{-\lambda}\lambda^k)/k!$ k=0,1, 2…P where: λ\lambdaλ is the average rate of occurrence per unit time or space, k is the number of occurrences is Euler's number (~2.718).

This distribution is suitable when events are independent, have a constant mean rate, and do not coincide.

Applications of Poisson Distribution in Medical Sciences

Disease Incidence and Rare Events

Poisson distribution is used to model the number of disease cases in a given population over a specific period.

Patient Arrivals in Emergency Departments

Hospitals use the Poisson distribution to estimate the number of emergency arrivals in a given time frame.

Medical Errors and Adverse Drug Reactions

Poisson distribution is also applied to estimate the frequency of medical errors in hospitals.

Mathematical Examples of Poisson Distribution in Medical Sciences

Example 1: Suppose a rare disease occurs in a city with an average of 2 cases per month. The probability of exactly 5 cases in a given month?

Computed as: λ=2 and k=5

$P(X=k)=(e^{-\lambda}\lambda^k)/k!$, $P(X=5)=(e^{(-2)}2^5)/5! = 0.03609$

Thus, there is a 3.609 % chance that 5 cases will be observed in a month.

Example 2: A hospital's emergency room receives an average of 10 patients per hour. The probability of receiving exactly 7 patients in an hour is:

$P(X=7) = e^{(-10)}10^7/7! = (0.0000454\times10000000)/5040 = 0.09008$

Thus, there is a 9.008% probability that 7 patients will arrive in an hour.

Example 3: A hospital records an average of 2 medication errors per day. The probability of observing zero errors in a day is:

$P(X=0) = e^{(-2)}2^0/0! = e^{-2} = 0.1353$

This means there is a 13.53% chance of having no medication errors on a given day.

Geometric Distribution

Theoretical Background of Geometric Distribution

The Geometric distribution is particularly useful when studying the waiting time until an event occurs, such as the first failure of a medical device or the time until a patient responds to treatment.

This article explores the mathematical formulation of geometric distribution and its applications in biostatistics, epidemiology, and clinical trials with illustrative examples.

Definition and Properties of Geometric Distribution

A random variable X follows a geometric distribution if it counts the number of Bernoulli trials required to achieve the first success. Mathematically, it is defined as:

$P(X=k) = (1-p)^{k-1}p, k=1,2,3, \ldots$

where: k is the number of trials until the first success, p is the probability of success in each trial, and q (q=1-p) is the probability of failure.

These properties help in estimating the average waiting time for an event and the variability in waiting times.

Applications of Geometric Distribution in Medical Sciences

Survival Analysis and Time until First Occurrence of Disease

In survival analysis, geometric distribution models the time (in discrete units) until the first occurrence of an event, such as disease onset or relapse.

Modelling the Number of Attempts Until a Successful Diagnosis

When diagnosing a disease, multiple tests may be required before a successful diagnosis is made.

Drug Response Time in Clinical Trials

In clinical trials, researchers often measure how long it takes for a patient to respond to a new drug.

Mathematical Examples of Geometric Distribution in Medical Sciences

Example 1: Time until First Cancer Relapse

Suppose the probability of a cancer relapse in any given month after treatment is 0.1 (p=0.1). The probability that a patient experiences the first relapse in the 5th month is:

$P(X=5) = (1-0.1)^{5-1}(0.1) = (0.9)^4 \times 0.1 = 0.0656$

Thus, there is a 6.56% chance that the patient will relapse in the 5th month.

Example 2: Number of Blood Tests until a Positive Diagnosis

A doctor orders blood tests for a rare infection, where each test has a 20% probability (p=0.2) of detecting the infection if the patient has it. The probability that the infection is first detected in the third test is:

$P(X=3) = (1-0.2)^{3-1}(0.2) = (0.8)^2 \times 0.2 = 0.128$

Thus, there is a 12.8% probability that the infection will be detected in the third test.

Example 3: Time until a Drug Shows Effectiveness

Suppose a new drug has a 30% probability (p=0.3) of working on a patient in any given week. The expected number of weeks until the drug is effective is:

$E(X)=1/p = 1/0.3=3.33$ weeks.

This means, on average, patients respond to the drug after about 3.33 weeks.

Hypergeometric Distribution

Theoretical Background of the Hypergeometric Distribution

Probability distributions play a vital role in medical research, where sampling without replacement is common. The hypergeometric distribution is crucial in analyzing medical trials, disease detection, and population studies where the total population is finite and samples are drawn without replacement. This contrasts with the binomial distribution, where sampling is done with replacement.

Definition of Hypergeometric Distribution

The Hypergeometric distribution models the probability of obtaining k successes in a sample of size n drawn from a finite population of size NNN, which contains K successful cases. It is defined as:

$$P(X=k)=\frac{\binom{K}{k}\binom{N-K}{n-k}}{\binom{N}{n}}$$

Where N = Total population size, K= Number of successful cases in the population, n = Sample size, k = Number of observed successes in the sample

This formula accounts for selecting without replacement, making it suitable for many medical applications.

Applications of the Hypergeometric Distribution in Medical Sciences

Disease Screening and Diagnostic Testing

Medical researchers often test for diseases in a group of patients. Suppose we want to determine the probability of selecting infected patients from a sample without replacement.

Drug Testing and Quality Control

In clinical trials, researchers randomly select patients from a population to test a new drug's efficacy. The hypergeometric distribution helps assess how likely it is to obtain a certain number of successful treatments in a sample.

Epidemiological Studies

The hypergeometric distribution is useful in contact tracing and epidemiological surveys, where health officials analyse disease spread in a finite group.

The binomial distribution assumes independent trials with replacement, while the hypergeometric distribution accounts for finite populations and sampling without replacement. The binomial distribution can approximate the hypergeometric distribution when the sample size is small relative to the population:

$$P(X=k) = \binom{n}{k} p^k (1-p)^{n-k}, \text{ where } p=K/N$$

For large populations where N>n, the binomial distribution is a good approximation. However, for medical trials with a small cohort, the hypergeometric distribution is more accurate.

Mathematical Examples Of Hypergeometric Distribution In Medical Sciences.

Example 1: Tuberculosis Screening

A hospital has N = 1000 patients, among whom K = 100 have tuberculosis (TB). If a doctor randomly selects n = 10 patients for an initial screening, what is the probability that exactly k = 3 of them have TB?

Using the hypergeometric formula:

$$P(X=3) = \frac{\binom{100}{3}\binom{1000-100}{10-3}}{\binom{1000}{10}} = \frac{\binom{100}{3}\binom{900}{7}}{\binom{1000}{10}} = 0.256$$

Using a statistical tool, the probability is approximately 0.256 (25.6%).

Example 2: Effectiveness of a New Drug:

A pharmaceutical company is testing a new drug on N = 200 patients, where K = 50 are expected to respond positively. If n = 20 patients are randomly selected, what is the probability that exactly k = 8 show positive effects?

Applying the hypergeometric formula:

$$P(X=8) = \frac{\binom{50}{8}\binom{200-50}{20-8}}{\binom{200}{20}} = \frac{\binom{50}{8}\binom{150}{12}}{\binom{200}{20}} = 117$$

Using statistical computation P(X=8) ≈0.117(11.7%).

Example 3: COVID-19 Contact Tracing: In a small town with N = 500 people, K = 50 were exposed to COVID-19. Health officials randomly test n = 30 people. What is the probability that exactly k = 5 of the tested individuals were exposed?

Applying the hypergeometric formula:

$$P(X=k) = \frac{\binom{K}{k}\binom{N-K}{n-k}}{\binom{N}{n}}$$

$$P(X=8) = \frac{\binom{50}{5}\binom{500-50}{30-5}}{\binom{500}{30}} = \frac{\binom{50}{5}\binom{450}{25}}{\binom{500}{30}} = 0.198$$

Using statistical computation, P(X=5) ≈ 0.198 (19.8%).

Theoretical Background of Negative Binomial Distributions

Count data in medical sciences, such as the number of infections, hospital visits, or gene mutations, often exhibit overdispersion, where variance exceeds the mean. The Poisson distribution, commonly used for modelling count data, assumes equidispersion (mean = variance), making it unsuitable in many cases. The Negative Binomial Distribution (NBD) generalizes the Poisson model by introducing an additional dispersion parameter, allowing for greater flexibility in modelling real-world medical data.

This article explores the mathematical foundation of the NBD, its derivation, and practical applications in medical sciences.

Definition and Mathematical Formulation

The Negative Binomial Distribution describes the probability of observing X failures before achieving r successes in a sequence of independent Bernoulli trials with success probability p.

Probability Mass Function (PMF)

For a discrete random variable X following a negative binomial distribution with parameters r (number of successes) and p (success probability per trial), the probability of observing X failures before the r th success is given by:

$$P(X=k) = \binom{k+r-1}{k} p^r (1-p)^k, \quad k=0,1,2,\ldots$$

where $\binom{k+r-1}{k}$ is the binomial coefficient:

$$\binom{k+r-1}{k} = (k+r-1)! \,/\, k!\,(r-1)!.$$

Mean and Variance:

The mean E[X] and variance Var(X) of a negative binomially distributed random variable are:

E[X]=r(1−p)/p, Var(X)= r(1−p) / p2

Since the variance exceeds the mean (Var(X)>E[X the NBD is ideal for modelling over-dispersed count data in medical studies.

Applications Of Negative Binomial Distributions In Medical Sciences

Modelling Disease Counts

In epidemiology, disease counts such as hospital admissions for respiratory illnesses often display overdispersion. If XXX represents the number of hospital visits before a patient recovers, it can be modelled as an NBD.

Gene Mutation Analysis

Genetic mutations in DNA sequences often occur sporadically and follow an overdispersed count pattern.

Modelling Infectious Disease Spread

The NBD is also used in epidemiology to model the transmission of infectious diseases. For example, the number of secondary infections caused by an infected individual often exhibits overdispersion due to variability in contact rates and immunity.

Mathematical Examples Of Negative Binomial Distributions In Medical Sciences

Example 1: Predicting Hospital Readmissions A hospital monitors patients recovering from a viral infection. The probability of full recovery per day is p=0.2, and the expected number of relapses before full recovery is modelled using r=3 (three successful health checkups before discharge).

Using the NBD formula, the probability that a patient experiences 5 relapses before full recovery is:

$$P(X=5) = \binom{5+3-1}{5} (0.2)^3(0.8)^5$$

$$P(X=5) = \binom{7}{5} (0.2)^3(0.8)^5$$

$$P(X=5) = 21\times0.008\times0.32768=0.055$$

Thus, there is a 5.5% probability that a patient will relapse 5 times before fully recovering.

Example 2: Counting DNA Mutations Suppose a biologist studies gene mutations occurring in a DNA sequence where each successful repair of a damaged strand happens with probability p=0.1, and they require 5 successful repairs before declaring the sequence stable.

The expected number of failures before achieving 5 repairs is:

E[X]=5(1−0.1)/0.1=45

The variance:

Var(X)=5(1−0.1)/0.12=450

Thus, the model predicts a highly variable number of mutations before a DNA sequence stabilizes, making the NBD a suitable choice.

Example 3: Secondary Infections in an Epidemic. Consider a viral outbreak where each infected individual spreads the disease until they recover. If the probability of transmitting the disease per interaction is p=0.3, and we observe the number of transmissions before an infected person recovers, then:

$$P(X=k) = \binom{k+4-1}{k} (0.3)^4(0.7)^k$$

For k=2, the probability of exactly 2 secondary infections before recovery is:

$$P(X=2) = \binom{5}{2} (0.3)^4(0.7)^k$$

P(X=2) =10×0.0081×0.49=0.0397

Thus, there is a 3.97% chance of exactly 2 secondary infections.

Advantages Of The Negative Binomial Distribution In Medical Sciences

Flexibility in Modelling Overdispersion – Unlike the Poisson distribution, the NBD allows for variance greater than the mean, making it suitable for highly variable medical data.

Realistic Modelling of Patient Data – It accurately captures scenarios where some patients experience more complications or longer recovery times.

Applicable to a Wide Range of Medical Fields – Useful in epidemiology, genetics, and healthcare management.

Conclusion

In conclusion, statistical discrete distributions serve as fundamental tools in the realm of medical research, offering the necessary mathematical frameworks to interpret complex biomedical data. These distributions, such as the Binomial, Poisson, Negative Binomial, and Geometric, among others, provide critical insights into various aspects of healthcare, from clinical trials to epidemiological studies and survival analysis. Their applications range from modelling binary outcomes like disease presence to assessing the probability of rare events and estimating time-to-event data, such as patient survival rates.

A thorough understanding of these distributions is not only essential for performing robust and accurate statistical analyses but also for ensuring ethical and effective decision-making in healthcare settings. As illustrated by mathematical examples, these distributions empower medical professionals and researchers to derive meaningful conclusions that inform treatment strategies, policy-making, and public health initiatives.

Moreover, the integration of these distributions into multivariable regression models further enhances their utility in addressing complex medical questions, fostering a deeper understanding of the relationships between variables. Ultimately, the significance of discrete statistical distributions extends beyond mere mathematical theory; they are indispensable tools that advance medical science, improve patient outcomes, and contribute to the ongoing evolution of evidence-based medicine.

By bridging theoretical concepts with real-world applications, this study emphasizes the vital role of statistical distributions in advancing medical research and underscores their enduring relevance in shaping healthcare decisions for the future.

References

1. Rao PS Statistical methodologies with medical applications. (2016a). Wiley Online Library: 2016a. doi 10.1002/9781119258568
2. Rao SR Applied Medical Statistics. Wiley-VCH Verlag;2016b.
3. Muth JE. Basic statistics and pharmaceutical statistical applications 2nd ed. Chapman & Hall/CRC; 2006.
4. Yan F. Robert M, Li Y., Statistical methods and common problems in medical or biomedical science research. International Journal of Physiology, Pathophysiology

and Pharmacology 2017;9(5), 157–163. PMID 29209453
5. Dinov ID. Data Science and Predictive Analytics: biomedical and health applications using R. 1st ed. Springer; 2018. Doi: 10.1007/978-3-319-72347-1.
6. Dinov ID. Data Science and Predictive Analytics: biomedical and health applications using R. 2nd ed. Springer; 2023. Doi: 10.1007/978-3-031-17483-4.
7. Krishnamoorthy, K. (2016). Handbook of Statistical Distributions with Applications (2nd ed.). CRC Press.
8. Taillie C, Patil GP, Baldessari BA. Statistical Distribution in Scientific Work: Applications in Physical, Social and Life Sciences. Springer Science & Business Media; 1981.
9. Shapiro SS, Brain CW. A Review of Distributional Testing Procedures and Development of a Censored Sample Distributional Test. In: Statistical Distributions in Scientific Work: Volume 5 - Inferential Problems and Properties. Springer; 1981. p. 1–24.
10. Walters SJ, Campbell MJ, Machin D. Medical Statistics: A Textbook for the Health Sciences. Wiley-VCH; 2021.
11. Kaniadakis G, Baldi MM, Deisboeck TS, Grisolia G, Hristopulos DT, Scarfone AM, et al. The k-statistics approach to epidemiology [Internet]. arXiv [q-bio.PE]. 2020. Available from: http://arxiv.org/abs/2012.00629
12. Ross SM. Introduction to Probability Models. Academic Press; 2014.
13. Medhi J. Stochastic Processes. New Age International; 1994.
14. Kleinbaum DG, Klein M. Survival Analysis: A Self-Learning Text. Springer; 2012.
15. Casella G, Berger RL. Statistical Inference. Brooks/Cole; 2002.
16. Rosner BA. Fundamentals of Biostatistics. Cengage Learning ; 2015.
17. Agresti A, Finlay B. Statistical Methods for the Social Sciences, Global Edition. Pearson; 2018.