

Probability Theory

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Chapter 08: Limit Theorems

Introduction

Limit Theorems

- The most important theoretical results in probability theory.
- The most important theorems are those classified either under
 - ★ *Laws of large numbers*
 - ★ *Central limit theorems*

Laws of large numbers

They are concerned with stating conditions under which the average of a sequence of RVs converges to the expected average.

Central limit theorems

They are concerned with determining conditions under which the sum of a large number of RVs has a probability distribution that is approximately normal.

Markov's Inequality

Proposition

If X is a RV that takes only nonnegative values, then, for any value $a > 0$,

$$P\{X \geq a\} \leq \frac{E[X]}{a}$$

Proof

For $a > 0$, let

$$I = \begin{cases} 1 & X \geq a \\ 0 & \text{otherwise} \end{cases}$$

Since $X \geq 0$,

$$I \leq \frac{X}{a}$$

Taking expectations of the preceding inequality yields

$$E[I] \leq \frac{E[X]}{a}$$

Since $E[I] = P\{X \geq a\}$,

$$P\{X \geq a\} \leq \frac{E[X]}{a} \quad \blacksquare$$

Chebyshev's Inequality

Proposition

If X is a RV with finite mean μ and variance σ^2 , then, for any value $k > 0$,

$$P\{|X - \mu| \geq k\} \leq \frac{\sigma^2}{k^2}$$

Proof

Since $(X - \mu)^2$ is a nonnegative random variable, we can apply Markov's inequality (with $a = k^2$) to obtain

$$P\{(X - \mu)^2 \geq k^2\} \leq \frac{E[(X - \mu)^2]}{k^2}$$

But since $(X - \mu)^2 \geq k^2$ if and only if $|X - \mu| \geq k$,

$$P\{|X - \mu| \geq k\} \leq \frac{E[(X - \mu)^2]}{k^2} = \frac{\sigma^2}{k^2} \quad \blacksquare$$

Examples

Suppose that it is known that the number of items produced in a factory during a week is a random variable with mean 50.

- What's the probability that this week's production will exceed 75?
- If the variance of a week's production is found to be 25, what's the probability that this week's production will be between 40 and 60?

Solution

Let X be the number of items that will be produced in a week.

- By Markov's inequality,

$$P\{X > 75\} \leq \frac{E[X]}{75} = \frac{50}{75} = \frac{2}{3}$$

- By Chebyshev's inequality,

$$P\{|X - 50| \geq 10\} \leq \frac{\sigma^2}{10^2} = \frac{25}{10^2} = \frac{1}{4}$$

$$P\{|X - 50| < 10\} \geq 1 - \frac{1}{4} = \frac{3}{4}$$

Examples (cont'd)

As Chebyshev's inequality is valid for all distributions of the random variable X , we cannot expect the bound on the probability to be very close to the actual probability in most cases.

Example

If $X \sim \text{Normal}(\mu, \sigma^2)$, Chebyshev's inequality states that

$$P\{|X - \mu| > 2\sigma\} \leq \frac{1}{4}$$

whereas the actual probability is given by

$$P\{|X - \mu| > 2\sigma\} = P\left\{\left|\frac{X - \mu}{\sigma}\right| > 2\right\} = 2(1 - \Phi(2)) \approx .0456$$

Chebyshev's inequality is often used as a theoretical tool in proving results.

The Weak Law of Large Numbers

Proposition

Let X_1, X_2, \dots, X_n be a sequence of i.i.d. RVs, each having finite mean $E[X_i] = \mu$. Then, for any $\varepsilon > 0$,

$$\lim_{n \rightarrow \infty} P \left\{ \left| \frac{X_1 + X_2 + \dots + X_n}{n} - \mu \right| \geq \varepsilon \right\} = 0$$

Part of the proof (X_i has finite variance σ^2)

Since

$$E \left[\frac{X_1 + X_2 + \dots + X_n}{n} \right] = \mu \quad \text{and} \quad \text{Var} \left(\frac{X_1 + X_2 + \dots + X_n}{n} \right) = \frac{\sigma^2}{n}$$

it follows from Chebyshev's inequality that

$$P \left\{ \left| \frac{X_1 + X_2 + \dots + X_n}{n} - \mu \right| \geq \varepsilon \right\} \leq \frac{\sigma^2}{n\varepsilon^2}$$

and the result is proven.

The Central Limit Theorem

The central limit theorem

Let X_1, X_2, \dots, X_n be a sequence of i.i.d. RVs, each having mean μ and variance σ^2 . If \bar{X} is the sample mean, then the distribution of

$$\frac{\bar{X} - \mu}{\sigma/\sqrt{n}}$$

tends to the standard normal as $n \rightarrow \infty$.

The central limit theorem

Let X_1, X_2, \dots, X_n be a sequence of i.i.d. RVs, each having mean μ and variance σ^2 . Then the distribution of

$$\frac{X_1 + X_2 + \dots + X_n - n\mu}{\sigma\sqrt{n}}$$

tends to the standard normal as $n \rightarrow \infty$.

Examples

If 10 fair dice are rolled, find the approximate probability that the sum obtained is between 30 and 40, inclusive.

Solution

Let X_i denote the value of the i^{th} die, $i = 1, 2, \dots, 10$. Since

$$E[X_i] = \frac{7}{2} \quad \text{Var}(X_i) = \frac{35}{12}$$

the central limit theorem yields

$$\begin{aligned} P\{29.5 \leq X \leq 40.5\} &= P \left\{ \frac{29.5 - 35}{\sqrt{\frac{350}{12}}} \leq \frac{X - 35}{\sqrt{\frac{350}{12}}} \leq \frac{40.5 - 35}{\sqrt{\frac{350}{12}}} \right\} \\ &\approx P\{-1.0184 \leq Z \leq 1.0184\} \\ &= \Phi(1.0184) - \Phi(-1.0184) \\ &= 2\Phi(1.0184) - 1 \quad \approx .692 \end{aligned}$$

Examples (cont'd)

An instructor has 50 exams that will be graded in sequence. The times required to grade the 50 exams are independent, with a common distribution that has mean 20 minutes and standard deviation 4 minutes. Approximate the probability that the instructor will grade at least 25 of the exams in the first 450 minutes of work.

Solution

If we let X_i be the time that it takes to grade exam i , then the time it takes to grade the first 25 exams is

$$X = \sum_{i=1}^{25} X_i$$

$$E[X] = \sum_{i=1}^{25} E[X_i] = 25(20) = 500$$

$$\text{Var}(X) = \sum_{i=1}^{25} \text{Var}(X_i) = 25(16) = 400$$

$$\begin{aligned} P\{X \leq 450\} &= P \left\{ \frac{X - 500}{\sqrt{400}} \leq \frac{450 - 500}{\sqrt{400}} \right\} \\ &\approx P\{Z \leq -2.5\} \\ &= 1 - \Phi(2.5) \quad \approx .006 \end{aligned}$$

The Strong Law of Large Numbers

The strong law of large numbers

Let X_1, X_2, \dots, X_n be a sequence of i.i.d. RVs, each having a finite mean $\mu = E[X_i]$. Then,

$$P \left\{ \lim_{n \rightarrow \infty} \frac{X_1 + X_2 + \dots + X_n}{n} = \mu \right\} = 1$$

Application

Suppose that a sequence of independent trials of some experiment is performed. Let E be a fixed event of the experiment.

Letting $X_i = \begin{cases} 1 & \text{if } E \text{ occurs on the } i^{\text{th}} \text{ trial} \\ 0 & \text{if } E \text{ does not occur on the } i^{\text{th}} \text{ trial} \end{cases}$

We have, by the strong law of large numbers, that with probability 1,

$$\frac{X_1 + X_2 + \dots + X_n}{n} \rightarrow E[X] = P(E)$$

The Weak Law vs. Strong Law of Large Numbers

Let X_1, X_2, \dots, X_n be a sequence of i.i.d. RVs (with finite mean $E[X_i] = \mu$).

The weak law of large numbers (WLLN)

$$\text{For any } \varepsilon > 0, \quad \lim_{n \rightarrow \infty} P \left\{ \left| \frac{X_1 + X_2 + \dots + X_n}{n} - \mu \right| \geq \varepsilon \right\} = 0$$

The strong law of large numbers (SLLN)

$$P \left\{ \lim_{n \rightarrow \infty} \frac{X_1 + X_2 + \dots + X_n}{n} = \mu \right\} = 1$$

The WLLN states that for any specified large value n^* , $(X_1 + X_2 + \dots + X_n)/n^*$ is likely to be near μ . However, it does not say that $(X_1 + X_2 + \dots + X_n)/n$ is bound to stay near μ for all values of n larger than n^* . Thus, it leaves open the possibility that large values of $|(X_1 + X_2 + \dots + X_n)/n - \mu|$ can occur infinitely often (though at infrequent intervals).

The SLLN shows that this cannot occur.