MATH 3338 Probability

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Lecture 9 - MATH 3338 Ch 9 Central Limit Theorem



Outline

Central Limit Theorem by examples

Central Limit Theorem for Continuous RVs

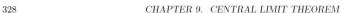
• Suppose A coin is tossed multiple times n with the indicator of head up $X_1, ..., X_n$, i.e. a Bernoulli Trial of n times with prob p > 0. Take the sum S_n , we have that S_n follows a Binomial distr with mean np, and variance np(1-p).

Now we take the standardized sums, by subtracting the mean np and dividing by its standard deviation $\sqrt{np(1-p)}$.

Definition 9.1 The standardized sum of S_n is given by

$$S_n^* = rac{S_n - np}{\sqrt{np(1-p)}}.$$

 S_n^* has mean 0 and variance 1. Because S_n takes values 0, 1, ..., n, there are n+1 values. We plot them with a height S_j^* for the j-th, we have a plot with a nice bell-curve as shown in the textbook p 327.



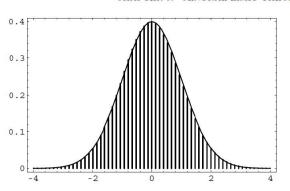


Figure 9.3: Corrected spike graph with standard normal density.

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We have the following theorem.

• **Theorem 9.1** (Central Limit Theorem for Binomial Distr) For the binomial distr Bin(n, p), we have

$$\sqrt{npq} \ b(n, p, \ll np + x\sqrt{npq} \gg) = \phi(x)$$

where $\ll np + x\sqrt{npq} \gg$ is the nearest integer close to $np + x\sqrt{npq}$, b(n,p,k) is the Binomial probability at the integer k, and $\phi(x)$ is the standard normal density function $\phi(x) = e^{-x^2/2}/\sqrt{2\pi}$.

• Approximating Binomial Distributions If we wish to find an approximation for binomial prob b(n, p, j), we set $j = p + x\sqrt{npq}$, and solve for x, obtaining $x = (j - np)/\sqrt{npq}$. By Theorem 9.1, $\sqrt{npq}b(n, p, j)$ is approximately equal to $\phi(x)$. so

$$b(n,p,j) = \phi(x)/\sqrt{npq} = rac{1}{\sqrt{npq}}\phi\left(rac{j-np}{\sqrt{npq}}
ight)$$

We have the following example.

• Example 9.2 A coin is tossed 100 times. Estimate the probability the the number of heads lies between 40 and 60 (inclusive). Solution The expected number of heads is 100(1//2) = 50 for fair coins. The standard deviation for the number of heads is $\sqrt{npq} = 5$. n = 100 is reasonably large, we have

$$P(40 \le S_n \le 60) = P\left(\frac{39.5 - 50}{5} \le S_n^* \le \frac{60.5 - 50}{5}\right)$$
$$= P(-2.1 \le S_n^* \le 2.1) = .9642$$

The actual number is .9648, is well approximated.



• Normal Approximation to Binomial Prob In general, the probability of binomial $S_n \sim Bin(n,p)$ is calculated by

$$P(i \leq S_n \leq j) = P\left(\frac{i - 1/2 - np}{\sqrt{np(1-p)}} \leq Z \leq \frac{j + 1/2 - np}{\sqrt{np(1-p)}}\right)$$

Consider two examples.

• **Uniform Distr** Let $X_1, ..., X_n$ be uniform RVs on [0,1]. Consider their sum $S_n = X_1 + ... + S_n$. $E(S_n) = n/2$, $Var(S_n) = n/12$. The standardized sum

$$S_n^* = \frac{S_n - n/2}{\sqrt{n/12}}$$

The standardized sum S_n^* has mean 0 and variance 1. $S_n^* \sim N(0,1)$, i.e. standard normal N(0,1) can be used to calculate the prob of S_n^* and then S_n .

• **Exponential Distr** Let $X_1, ..., X_n$ be exponential RVs $Exp(\lambda)$ with parameter $\lambda > 0$. Consider their sum $S_n = X_1 + ... + S_n$. $E(S_n) = n/\lambda$, $Var(S_n) = n/\lambda^2$ The standardized sum

$$S_n^* = \frac{S_n - n/\lambda}{\sqrt{n}/\lambda}$$

The standardized sum S_n^* has mean 0 and variance 1

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$$S_n^* = \frac{S_n - n/\lambda}{\sqrt{n}/\lambda}$$

The density functions of the sum S_n and the standardized sum S_n^* are

$$f_{S_n}(x) = \frac{\lambda e^{-\lambda x} (\lambda x)^{n-1}}{(n-1)!},$$

$$f_{S_n^*}(x) = \frac{\sqrt{n}}{\lambda} f_{S_n}\left(\frac{\sqrt{n}x + n}{\lambda}\right).$$

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• **Theorem 9.6** (Central Limit Theorem) Let $S_n = X_1 + ... + X_n$ be the sum of n indep continuous RVs with common density function p with expected value μ and variance σ^2 . Let $S_n^* = (S_n - n\mu)/\sqrt{n}\sigma$. Then for all a < b,

$$\lim_{n \to \infty} P(a < S_n^* < b) = \frac{1}{\sqrt{2\pi}} \int_a^b e^{-x^2/2} dx.$$

Note This theorem implies that for any distribution with finite mean and variance, this theorem applies, regardless of what distribution, symmetric or not, including Normal, uniform, exponential, chi-squares, etc.

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• **Example 9.9** A surveyor wants to measure a known distance, say of 1 mile, using some method with n observations. He notices that the mean is $\mu=1$, and the standard deviation $\sigma=0.0002$. If n is large, the average S_n/n has a density function approximately normal, with mean $\mu=1$ mile, and standard deviation $\sigma/\sqrt{n}=.0002/\sqrt{n}$.

Q: How many measures need to be made to make sure that his average lies within .0001 of the true value? Solution. Take the error bound to be the distance $\varepsilon=.0001$. By

the Chebyshev inequality,

$$P\left(\left|\frac{S_n}{n}-\mu\right|\geq \varepsilon\right)\leq \frac{.0002^2}{n\varepsilon^2}=\frac{4}{n},$$

To make sure that his average will be within a distance of ε , we often need to make sure the above prob to be out of the distance ε smaller than .05, i.e. $4/n \le .05$. Then $n \ge 4/.05 = 80$ But such an estimate by the Chebyshev inequality is too large.

Example 9.9

Solution. We need to solve it within the probability using the CLT, i.e.

$$P\left(\left|\frac{S_n}{n} - \mu\right| < \varepsilon\right) \ge .95$$

Now we need to calculate the probability using CLT.

$$P\left(\left|\frac{S_n}{n} - \mu\right| < \varepsilon\right) = P\left(\frac{\left|\frac{S_n}{n} - \mu\right|}{\sigma/\sqrt{n}} < \frac{\varepsilon}{\sigma/\sqrt{n}}\right) = .95$$

$$P(|Z| \le \frac{\varepsilon}{\sigma/\sqrt{n}}) = .95 \to \frac{\varepsilon}{\sigma/\sqrt{n}} = 1.96$$

$$n = \left(\frac{1.96\sigma}{\varepsilon}\right)^2 = 16$$
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Lecture 9 - MATH 3338 Ch 9 Central Limit 12/13

Estimating population mean with sample mean

The sample mean $\overline{X} = (X_1 + ... + X_n)/n$ can be used to estimate the population mean μ .

$$P(|\overline{X} - \mu| < \varepsilon) = .95$$

It implies that

$$P(\overline{X} - \varepsilon \le \mu \le \overline{X} + \varepsilon) = .95$$

that is the random interval $[\overline{X} - \varepsilon, \ \overline{X} + \varepsilon]$ has a 95% probability to contain the population μ , and thus the interval $[\overline{X} - \varepsilon, \ \overline{X} + \varepsilon]$ is called a 95% confidence interval of the population mean μ .

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