STA220H1: The Practice of Statistics I

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Please turn on your videos :)



Figure 1: [picture source]

Announcements

- 1. Submit your regrade requests on Crowdmark by Thursday.
- 2. Midterm 2 is in two weeks! Same logistics (the review session will be held online this time).

Agenda for today

- Recap: normal distribution, sample mean distribution and CLT
- More about CLT
- Confidence intervals

Recap: expectation and variance

Expectation

If X is a random variable and a is a number then

$$E(a\cdot X)=a\cdot E(X)$$

If Y is also a random variable then

$$E(X+Y)=E(X)+E(Y)$$

Variance

If X is a random variable and a is a number then

$$Var(a \cdot X) = a^2 \cdot Var(X)$$

▶ If Y is also a random variable and it is independent of X then

$$Var(X + Y) = Var(X) + Var(Y)$$

Recap: expectation and variance

If X_1, \ldots, X_n are independent random variables with $E(X_i) = \mu$ and $Var(X_i) = \sigma^2$ and $\bar{X} = \frac{X_1 + \ldots + X_n}{n}$ is the average of these random variables then

$$E(ar{X})=\mu$$
 and $Var(ar{X})=rac{\sigma^2}{n}$

Recap: density curves

We use **density curves** to describe the distribution of continuous random variables:

- The total area under the density curve is always 1
- ► The area under the curve bounded by a and b vertical lines is equal to P(a ≤ X ≤ b)



Recap: normal distribution

Normal random variable $X \sim Normal(\mu, \sigma^2)$ has symmetric, bell-shaped and unimodal distribution.

μ = E(X) controls the "center" of the distribution
 σ² = Var(X) controls the "spread" of the distribution



Recap: normal distribution

Standard normal distribution has $\mu = 0$ and $\sigma^2 = 1$.

► To find the probabilities P(a ≤ X ≤ b) for standard normal we use the distribution table

$$P(-1 \le X \le 1.25) =$$



Recap: normal distribution

If X ~ Normal(μ, σ²) we use standardization. The transformed variable Y = X-μ/σ has standard normal distribution.

For example, if $X \sim Normal(1, 100)$

 $P(-6 \le X \le 6) =$

We want to study the **population parameter** μ , e.g. the average life expectancy in Canada.

We take a **sample** of n people and compute the average age of death for them.

Black dots: sample x_1, \ldots, x_n

Red dot: sample mean $\bar{x} = \frac{x_1 + \dots + x_n}{n}$



If your sample size is small (e.g. n = 3), then \bar{x} can significantly vary from sample to sample.



If your sample size is large (e.g. n = 100), then the variation in \bar{x} is less considerable.

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age of death (years)				



Can we characterize the behavior of \bar{x} ?

Recap: alternative view

- We have *n* random variables X_1, \ldots, X_n
- We assume that they have the same distribution with $E(X_i) = \mu$ and $Var(X_i) = \sigma^2$
- We consider $\bar{X} = \frac{X_1 + \dots + X_n}{n}$, it is a random variable
- Each sample mean \bar{x} is a realization of \bar{X}

What is the probability density of \bar{X} ?



Recap: central limit theorem

Central limit theorem: for *n* large enough

$$ar{X}$$
 approximately $\sim \textit{Normal}\left(\mu, rac{\sigma^2}{n}
ight)$

- ▶ For different samples \bar{x} will "jump around" μ
- The larger the sample size the closer \bar{x} to μ



CLT applies to almost all types of probability distributions.

Example: the probability to win a lottery ticket is p. Suppose we buy n tickets and compute the **proportion of winning tickets**.

- X₁,..., X_n ~ Bernoulli(p) is the outcome for each ticket
 Y = X₁ + ... + X_n ~ Binomial(n, p) is the total number of winning tickets
- $\bar{X} = \frac{Y}{n}$ is the proportion of winning tickets

What is the distribution for the proportion of winning tickets?

Exercise

The probability to win in a lottery p. Suppose we buy n tickets. $E(\bar{X}) =$

$$Var(\bar{X}) =$$

Central limit theorem: more examples

Example: n = 5 and p = 0.1. Note that \overline{X} has discrete distribution.



Central limit theorem: more examples

Example: n = 10 and p = 0.1. Note that \overline{X} has discrete distribution.



Central limit theorem: more examples

Example: n = 100 and p = 0.1. Note that if n is large enough

- For different samples the proportion of winning tickets will "jump around" p
- The larger the sample size the closer the proportion of winning tickets to p



Confidence intervals

We want to study the average life expectancy in Canada.

We take a sample of 25 people and record their ages of death

ages

[1] 74.7 82.8 72.6 97.0 84.3 72.8

We compute the sample mean for these 25 people

mean(ages)

[1] 82.7

We claim that it is an **estimate** of the average life expectancy in Canada. *How confident are we in our estimate?*

Confidence intervals CLT:

$$ar{X}$$
 approximately $\sim \textit{Normal}\left(\mu, rac{\sigma^2}{n}
ight)$

Standardization:

$$rac{ar{X}-\mu}{\sigma/\sqrt{n}}$$
 approximately \sim *Normal* (0,1)

Distribution table:

$$P\left(-1.96 \leq rac{ar{X}-\mu}{\sigma/\sqrt{n}} \leq 1.96
ight) = 0.95$$

Interval for μ :

$$P\left(\bar{X} - 1.96 \cdot \frac{\sigma}{\sqrt{n}} \le \mu \le \bar{X} + 1.96 \cdot \frac{\sigma}{\sqrt{n}}\right) = 0.95$$

95% confidence interval for μ :

$$\left[\bar{x} - 1.96 \cdot \frac{\sigma}{\sqrt{n}}, \bar{x} + 1.96 \cdot \frac{\sigma}{\sqrt{n}} \right]$$



How to find 90% confidence interval? How to find 80% confidence interval?

95% confidence interval for μ :

$$\left[ar{x}-1.96\cdotrac{s}{\sqrt{n}},ar{x}+1.96\cdotrac{s}{\sqrt{n}}
ight]?$$

sd(ages)

[1] 9.5

Alternative view

- We have *n* random variables X_1, \ldots, X_n
- $\bar{X} = \frac{1}{n} \sum_{i=1}^{n} X_i$ is a random variable
- Each sample mean \bar{x} is a realization of \bar{X}
- $S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i \bar{X})^2$ is a random variable
- Each sample variance s^2 is a realization of S^2

Standardization:

$$rac{ar{X}-\mu}{S/\sqrt{n}}$$
 approximately $\sim t_{n-1}$

- "t distribution with n-1 degrees of freedom"
- It is similar to normal, but not quite...

Normal: a = 1.96 t with df = 3: a = 3.18 t with df = 10: a = 2.23 t with df = 50: a = 2.01



95% confidence interval for μ :

$$\left[\bar{x} - a \cdot \frac{s}{\sqrt{n}}, \bar{x} + a \cdot \frac{s}{\sqrt{n}}\right]$$

Where a is found from the distribution table.



How to find 90% confidence interval? How to find 80% confidence interval?

Confidence intervals: more examples

We want to estimate the probability to win in the lottery.

We take a sample of 50 tickets and record the outcomes (1 - win, 0 - lose)

tickets

[1] 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0

We compute the sample mean for these 50 outcomes (i.e. proportion of winning tickets)

mean(tickets)

[1] 0.08

We claim that it is an **estimate** of the probability to win the lottery. *How confident are we in our estimate?*

Confidence intervals: more examples

CLT:
$$\bar{X}$$
 approximately $\sim Normal\left(p, \frac{p(1-p)}{n}\right)$

95% confidence interval for p (known σ):

$$\left[ar{x} - 1.96 \cdot rac{\sigma}{\sqrt{n}}, ar{x} + 1.96 \cdot rac{\sigma}{\sqrt{n}}
ight]$$

95% confidence interval for p (unknown σ):

$$\left[\bar{x} - 1.96 \cdot \sqrt{\frac{\bar{x}(1-\bar{x})}{n}}, \bar{x} + 1.96 \cdot \sqrt{\frac{\bar{x}(1-\bar{x})}{n}}\right]$$



How to find 90% confidence interval? How to find 80% confidence interval?

TO DO

- 1. Module 6. Confidence Intervals Part 1 and Module 7. Confidence Intervals Part 2
- 2. Quiz 7 due Monday (March 6) @ 11:59 PM (EST)
- 3. Practice Problem Set 7