

Chapter 7. Sampling Distributions



February 18, 2022

1 7.1 Point Estimation

2 7.2 Central Limit Theorem

Statistical inference is concerned with making **decisions** about a population based on the information contained in a random sample from that population.

Before the data are collected, the observations are considered to be random variables, say X_1, X_2, \dots, X_n .

Definition

- (1) **Statistic** is a function of the observation. Statistic is also a random variable. For example, the sample mean and the sample variance are statistic. (\bar{X}, S)
- (2) **Sampling distribution** is the probability distribution of a statistic.

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- (4) If X is a random variable with probability distribution , characterized by the unknown parameter θ , and if X_1, X_2, \dots, X_n is a random sample of size n from X , the statistic $\hat{\Theta} = h(X_1, X_2, \dots, X_n)$ is called a **point estimator** of θ .

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Populations (parameters need estimate)	Samples of size n (point estimators)
Mean μ	sample mean \bar{x}
Variance σ^2	Sample variance s^2
Proposition p of interested items	Sample proposition $\hat{p} = x/n$, x the number of interested items
Difference of means $\mu_1 - \mu_2$	Difference of sample means $\bar{x}_1 - \bar{x}_2$
Difference of proposition $p_1 - p_2$	Difference of sample propositions $\hat{p}_1 - \hat{p}_2$

Theorem

If X_1, X_2, \dots, X_n is a random sample of size n taken from a **normal population** (either finite or infinite) with mean μ and finite variance σ^2 .
The the sample mean (random variable)

$$\bar{X} = \frac{X_1 + X_2 + \dots + X_n}{n}$$

has a normal distribution with

- mean

$$\mu_{\bar{X}} = \frac{\mu + \mu + \dots + \mu}{n} = \mu$$

- variance

$$\sigma_{\bar{X}}^2 = \frac{\sigma^2 + \sigma^2 + \dots + \sigma^2}{n^2} = \frac{\sigma^2}{n}.$$

Note. If X and Y are two independent random variables then

$$\mu_{aX+bY} = a\mu_X + b\mu_Y$$

$$\sigma_{aX+bY}^2 = a^2\sigma_X^2 + b^2\sigma_Y^2$$

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Example

The amount of time required for an oil and filter change on an automobile is normally distributed with a mean of 28 minutes and a standard deviation of 5 minutes. A random sample of 16 cars is selected. What is the probability that the sample mean is greater than 29?

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Example

The amount of time required for an oil and filter change on an automobile is normally distributed with a mean of 28 minutes and a standard deviation of 5 minutes. A random sample of 16 cars is selected. What is the probability that the sample mean is greater than 29?

Answer: The sample mean has a normal distribution with:

$$\mu_{\bar{X}} = 28, \sigma_{\bar{X}} = \frac{5}{\sqrt{16}} = 1.25$$

We want to compute $P(\bar{X} > 29)$. (Set $Z = \frac{\bar{X}-28}{1.25}$ is standard normal)

$$P(\bar{X} > 29) = P(Z > (29 - 28)/1.25) = P(Z > 0.8) = 1 - \Phi(0.8) = 0.212$$

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Example

To determine the difference, if any, between two brands of radial tires, 16 tires of first brand (X) and 25 tires of second brand (Y) are tested. Assume that the lifetimes of both brands of tires come from the same normal distribution $N(90000, 25000)$. What is the distribution of the difference of the sample means $\bar{X} - \bar{Y}$?

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Answer. We have \bar{X}, \bar{Y} has normal distributions with

$$\mu_{\bar{X}} = 90000, \sigma_{\bar{X}}^2 = \frac{25000}{16} = 1562.5$$

$$\mu_{\bar{Y}} = 90000, \sigma_{\bar{Y}}^2 = \frac{25000}{25} = 1000$$

Hence $\bar{X} - \bar{Y}$ has a normal distribution with

$$\mu_{\bar{X} - \bar{Y}} = \mu_{\bar{X}} - \mu_{\bar{Y}} = 0$$

$$\sigma_{\bar{X} - \bar{Y}}^2 = \sigma_{\bar{X}}^2 + \sigma_{\bar{Y}}^2 = 1562.5 + 1000 = 2562.5$$

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Theorem (Central Limit Theorem)

Suppose X_1, X_2, \dots, X_n is a random sample of size n taken from a population (either finite or infinite) with mean μ and finite variance σ^2 . Let

$$\bar{X} = \frac{X_1 + X_2 + \dots + X_n}{n}$$

be the sample mean. Then

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

approximate **standard normal** when n large ($n \geq 30$).

It means as $n \geq 30$, we can consider \bar{X} has a normal distribution with mean μ and variance σ^2/n .

Example

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Answer: The average salary \bar{X} of the 100 players has

$$\mu_{\bar{X}} = 1.5, \sigma_{\bar{X}} = \frac{0.9}{\sqrt{100}} = 0.09$$

Hence

$$Z = \frac{\bar{X} - 1.5}{0.09}$$

is approximated the standard normal. Thus,

$$\begin{aligned} P(\bar{X} \leq 1.4) &= P(Z \leq (1.4 - 1.5)/0.09) \\ &= P(Z \leq -1.111) = \Phi(-1.111) = 0.133 \end{aligned}$$

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