

Confidence Intervals & Hypothesis Testing

- Briefly: Where are we & where are we going
- CLT and 95% confidence intervals
- Hypothesis testing in general
- Hypothesis testing of one mean



Review of the Normal Distribution

- For normal distribution

- Stata calculates $P(Z < z)$

- If you have a z-value and you want p [$P(Z < z)$], use

```
display normal(z)
di normal(1.96)
.9750021
```

- If you have a z-value and you want p [$P(Z > z)$], use

```
display 1-normal(z)
di 1-normal(1.96)
.0249979
```

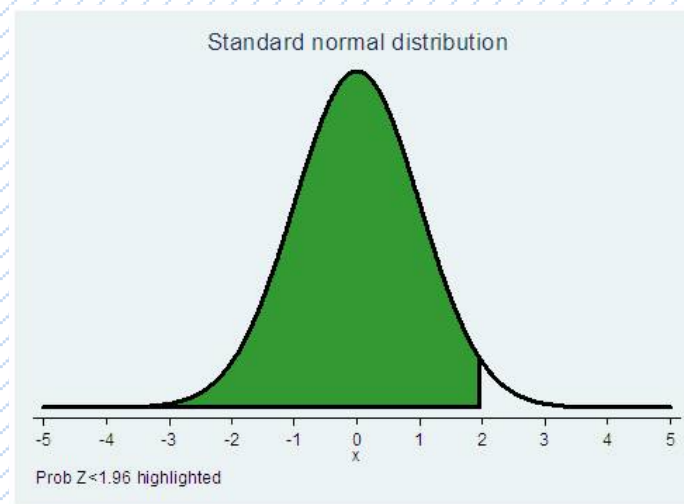
- If you have p [$P(Z < z)$] and you want z-value, use

```
display invnormal(p)
. di invnormal(.975)
1.959964
```

- If you have p [$P(Z > z)$] and you want z-value, use

```
display invnormal(1-p)
di invnormal(.025)
-1.959964
```

Or use what you know about the symmetry of the distribution



Review of Student's t Distribution

- For t distribution

- Stata calculates $P(T > t)$ for each d.f.

- If you have a t value and you want p [$P(T > t)$], use

```
display ttail(df,t)
di ttail(99,1.96)
.02640356
```

- If you have a t value and you want p [$P(T < t)$], use

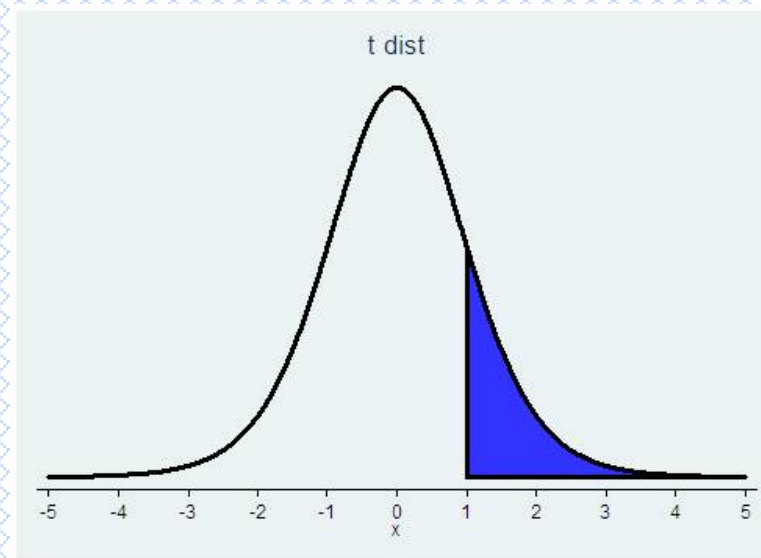
```
display 1-ttail(df,t)
di 1-ttail(99,1.96)
.97359644
```

- If you have p [$P(T > t)$] and you want t-value, use

```
display invttail(df,p)
di invttail(99,.025)
1.984217
```

- If you have p [$P(T < t)$] and you want t value, use

```
display invttail(df,1-p)
di invttail(99,.975)
-1.984217
```



Or use what you know about the symmetry of the distribution

Confidence intervals

- Knowing the distribution of the sample means we write down

$$P(-1.96 \leq \frac{\bar{X} - \mu}{\sigma / \sqrt{n}} \leq 1.96) = 0.95$$

and do the math to rearrange

$$P(\bar{X} - 1.96\sigma / \sqrt{n} \leq \mu \leq \bar{X} + 1.96\sigma / \sqrt{n}) = 0.95$$

- If you had drawn your sample 100 times, approximately 95 of the confidence intervals would include the true population mean μ .
 - *The interval is random.*
- These intervals can be derived for any point estimate, e.g. risk ratio, rate, etc. with known distribution.
- We use either z or t depending on whether the variance is known

Confidence intervals for proportions

- As n increases, the binomial distribution approaches the normal distribution
- Also, as n increases, the distribution of an estimated proportion approaches the normal distribution
 - $x/n = \hat{p} \sim N(p, \sqrt{p(1-p)/n})$
 - x/n is the proportion of successes
 - p is the population proportion
 - $\sqrt{p(1-p)/n}$ is the standard deviation of x/n if X is binomial
- So we can use the normal distribution to calculate confidence intervals for p
 $\hat{p} - 1.96 * \sqrt{\hat{p}(1 - \hat{p})/n} , \hat{p} + 1.96 * \sqrt{\hat{p}(1 - \hat{p})/n}$

Confidence intervals for proportions

- But if n is small or p is small or both then the normal approximation is not good and the intervals using the normal approximation are not good
- We need to use the binomial distribution
- Confidence intervals using the binomial distribution are called exact confidence intervals
- Exact confidence intervals are not symmetric around $\hat{p}$ (because the binomial distribution is not symmetric for small n or small p)

****Hypothesis testing****

- Confidence intervals tell us about the uncertainty in a point estimate of the population mean or proportion
- Hypothesis testing allows us to draw a conclusion about a population parameter that we have estimated in a sample
- Remember, we are taking samples from the population and we never know the truth.

*****some journals now ONLY want confidence intervals*****

Statistical hypothesis tests: cheat sheet

Data and comparison type	Alternative hypotheses	Parametric test Stata command
Numerical; One mean	$H_a: \mu \neq \mu_a$ (two-sided) $H_a: \mu > \mu_a$ or $\mu < \mu_a$ (one-sided)	Z or t-test • <code>ttest var1==hypoth val *</code>
Numerical; Two means, <u>paired data</u>	$H_a: \mu_1 \neq \mu_2$ (two-sided) $H_a: \mu_1 > \mu_2$ or $\mu < \mu_a$ (one-sided)	Paired t-test • <code>ttest var1==var2*</code>
Numerical; Two means, independent data	$H_a: \mu_1 \neq \mu_2$ (two-sided) $H_a: \mu_1 > \mu_2$ or $\mu < \mu_a$ (one-sided)	T-test (equal or unequal variance) • <code>ttest var1, by(byvar)</code> • <code>ttest var1, by(byvar) unequal</code>
Numerical, Two or more means, independent data		
Dichotomous; One proportion	$H_a: p \neq p_a$ (two-sided) $H_a: p > p_a$ or $p < p_a$ (one-sided)	Proportion test • <code>prtest var1=hypoth value*</code> • <code>bitest var1=hypoth value</code>
Dichotomous; two proportions	$H_a: p_1 \neq p_2$ (two-sided) $H_a: p_1 > p_2$ (one-sided)	Proportion test (z-test) • <code>prtest var1, by(byvar)</code>

Hypothesis testing for a mean

- To conduct a hypothesis test about the mean of a population, we hypothesize a value for it, and call that value μ_0 .
 - We write this $H_0 : \mu = \mu_0$
 - We call this the null hypothesis
- We set an alternative hypothesis for all other values of μ
 - We write this: $H_A : \mu \neq \mu_0$
 - We call this the alternative hypothesis
- We set the probability of incorrectly rejecting the null that we are willing to live with in advance, *before collecting the data and doing the analysis*
- That probability is called the *significance level*
- The significance level is denoted by α or alpha, and is frequently set to 0.05 or 5% error

Hypothesis testing

- In hypothesis testing, a true null hypothesis might be mistakenly rejected (if the sample you drew was very different from the null just by chance)
- This mistake is called a Type I error
 - The probability of a Type I error is chosen in advance
 - This probability is called the significance level, α

The probability of obtaining a mean at or more extreme than the observed mean, *given that the null hypothesis is true*, is the p-value of the test.

Basic steps in Hypothesis testing

- Before the test, set the significance level, α
 - This is the probability of rejecting the null hypothesis when it is true P(Type I error) that you can live with
- When you run the test, you get a probability of observing a sample mean as extreme as you did, given that the null hypothesis is true
 - This probability is the p-value
- If the p-value is less than α , (e.g. $\alpha=0.05$ and $p=0.013$), then the test is called statistically significant and the null hypothesis is rejected

Hypothesis Testing

1. State the hypotheses

- H_0 (the null hypothesis) and H_A (the alternative hypothesis) must be mutually exclusive (no overlap) and include all the possibilities
- The alternative is the complement of the null

2. Determine the compatibility with the null hypothesis

- We determine if there is enough evidence to reject the null hypothesis (i.e. calculate the test statistic and find the p-value)
 - If the null hypothesis is true, what is the probability of obtaining the sample data as extreme or more extreme?
 - Calculate a test statistic
 - Find the probability of the test statistic if the null is true
- *This probability is called the p-value*

Hypothesis Testing

3. Reject or fail to reject

- If the p-value (the probability of obtaining the sample data and corresponding test statistic if the null hypothesis is true) is sufficiently small (we often use 5%) then we reject the null and say the test was statistically significant.
- This 5% is α , the significance level
- *If we fail to reject the null hypothesis, it does not mean that we accept it.*

Hypothesis Testing of one mean

- We want to test whether a mean is equal to an hypothesized value
 - If we believe there might be deviations in either direction, we use a two-sided test
 - Two sided test:
 - Null hypothesis: $H_0: \mu = \mu_0$
 - Alternative hypothesis: $H_A: \mu \neq \mu_0$
 - If we only care about values above or below a certain value, we use a one-sided test
 - One sided test:
 - Null hypothesis: $H_0: \mu \geq \mu_0$
 - Alternative hypothesis: $H_A: \mu < \mu_0$
- or
- Null hypothesis: $H_0: \mu \leq \mu_0$
 - Alternative hypothesis: $H_A: \mu > \mu_0$

Hypothesis Testing of one mean

- The distribution of the sample mean $\bar{x}$ if n is large enough is normal by the CLT. So you can calculate the z statistic:

$$z_{stat} = \frac{\bar{x} - \mu_0}{\sigma / \sqrt{n}}$$

If σ is not known, calculate

$$t_{stat} = \frac{\bar{x} - \mu_0}{s / \sqrt{n}}$$

Hypothesis Testing of one mean: one-sided

Non-pneumatic anti-shock garment for the treatment of obstetric hemorrhage in Nigeria

- Mean initial blood loss 1413.1 ml; SD=491.3; n=83
- Our question: Are these women sampled from a population that is hemorrhaging (>750 ml blood loss)?

Hypothesis Testing of one mean: one-sided

- The null hypothesis is they are not hemorrhaging

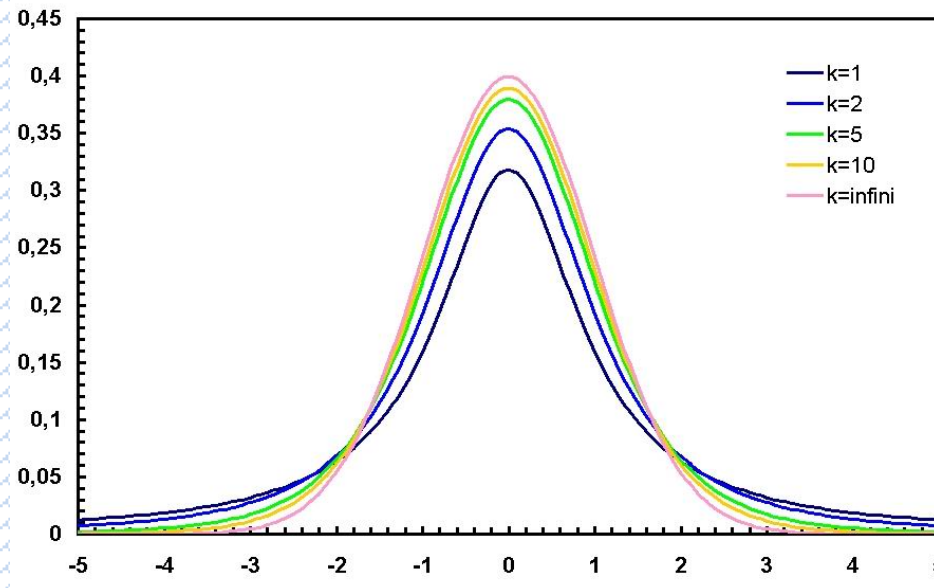
$$H_0: \mu \leq 750 \quad H_A: \mu > 750 \quad \alpha = 0.05$$

- T-statistic:

$$t_{stat} = \frac{\bar{X} - \mu_0}{s / \sqrt{n}} \\ = \frac{1413.1 - 750}{491.3 / \sqrt{83}} = 12.3$$

- p-value: $P(t > 12.3)$ with 82 d.f.

Hypothesis Testing of one mean

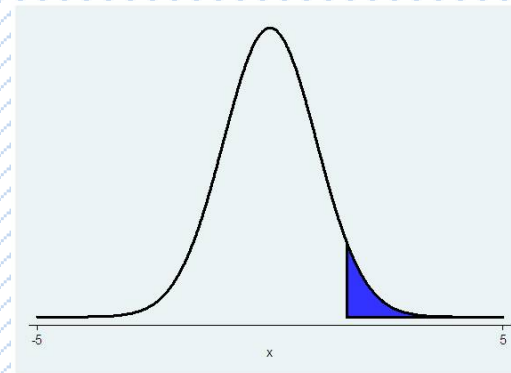


- 12.3 is off the graph
- So the probability of observing a sample mean of 1413 with $n=83$ and $SD=431$ if the true mean is ≤ 750 is very very low

Hypothesis Testing of one mean: one-sided

$P(T > \text{test stat})$

```
. display ttail(82, 12.3)  
1.308e-20
```



The p-value is < 0.001 , which is a lot less than 0.05, therefore we reject the null

Hypothesis Testing of one mean: one-sided

Another way: Stata *calculate* code for ttests:

ttesti samplesize samplemean samplesd hypothesizedmean

```
ttesti 83          1413.1      491.3      750
```

One-sample t test

	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
x	83	1413.1	53.92718	491.3	1305.822	1520.378

mean = mean(x)

Ho: mean = 750

Ha: mean < 750
Pr(T < t) = 1.0000

Ha: mean != 750
Pr(|T| > |t|) = 0.0000

t = 12.2962
degrees of freedom = 82

Ha: mean > 750
Pr(T > t) = 0.0000

Stata gives you 3
alternative hypotheses

→ We reject the null hypothesis