

Hypothesis tests for one parameter

1

Couple of definitions

- Standard normal distribution
 $z_i \sim N(0,1)$
- Normal distribution
 $y_i \sim N(\mu, \sigma^2)$
- Normal can always be turned into a standard normal by subtracting mean and dividing by standard deviation
 $z_i = (y_i - \mu) / \sigma \sim N(0,1)$

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Some Prob/Stat Review

- y_i is a normal random variable
- $y_i \sim N(0, \sigma^2)$
- Suppose there are n independent y_i 's

$$W_1 = \sum_{i=1}^n y_i$$

- Then $W_1 \sim N(0, n\sigma^2)$
- (Last question on Problem set #1)

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Likewise

- $y_i \sim N(0, \sigma^2)$
- Suppose there are n independent y_i 's

$$W_2 = \sum_{i=1}^n b_i y_i$$

- Where b_i is a constant

$$W_2 \sim N \left[0, \left(\sum_{i=1}^n b_i^2 \right) \sigma^2 \right]$$

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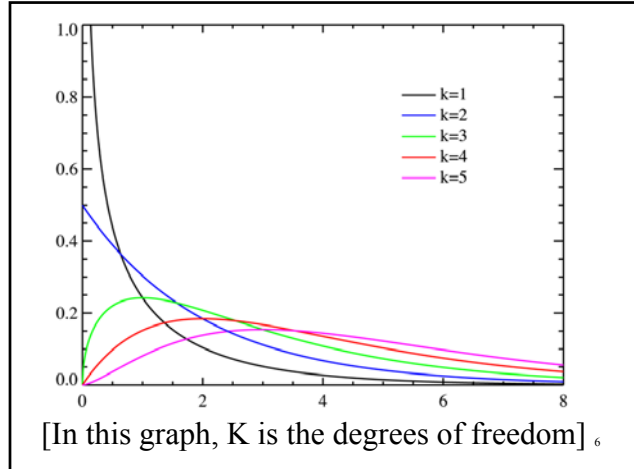
Some Prob/Stat Review

- z_i is a standard normal random variable
- $z_i \sim N(0,1)$
- Suppose there are n independent z_i 's

$$W_3 = \sum_{i=1}^n z_i^2$$

- Then W_3 is a Chi-squared random variable with n degrees of freedom

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- Suppose
 - W_k is a chi-squared distribution with k degrees of freedom
 - W_n is a chi-squared distribution with n degrees of freedom
- Then $S = (W_k/K) / (W_n/n)$ is an F distribution with (k,n) degrees of freedom
- Defined over all $S > 0$

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- Suppose z is standard normal $z \sim N[0,1]$
- Suppose W is a chi-squared with n degrees of freedom

$$t = \frac{z}{\sqrt{\frac{W}{n}}}$$

is distributed as a student t with n DOF

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Student t

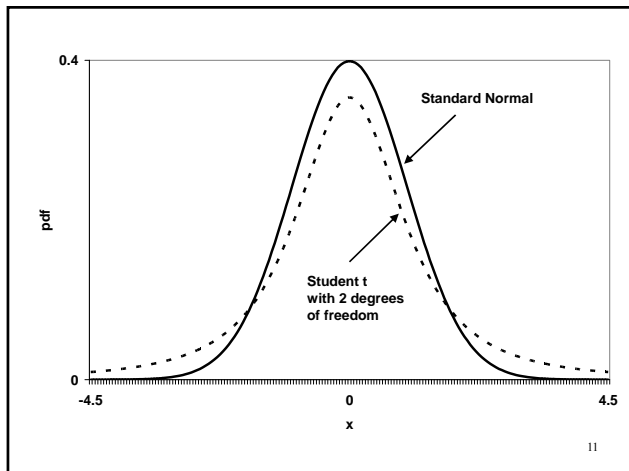
- William Sealy Gosset
– (1876-1937)
- Statistician
- Employee of Guinness
- Used statistical models to isolate the highest yielding varieties of barley
- [Homer](#) is correct



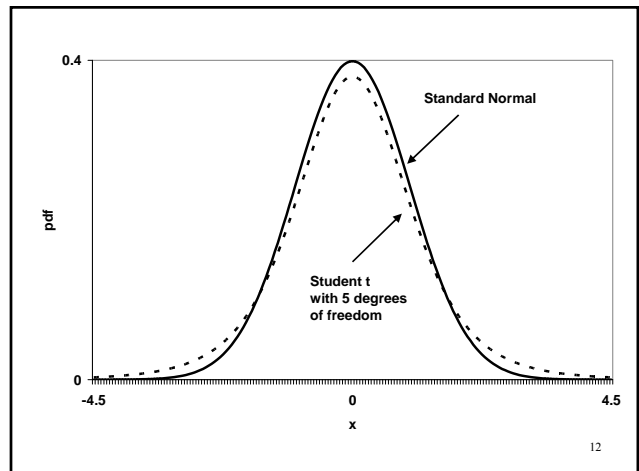
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- Symmetric, uni-modal PDF
- Defined over all real numbers
- Shape is a function of the degrees of freedom
- Sigmoid CDF
- $E[t]=0$
- $V[t]>1$ but approaches 1 as DOF approach ∞
- PDF shape very similar to standard normal with “fatter tails”

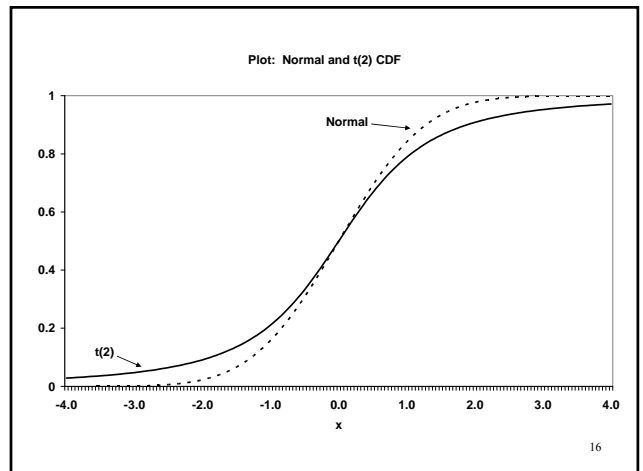
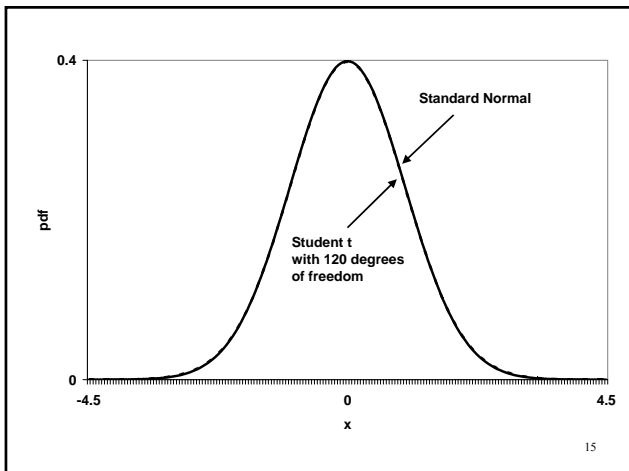
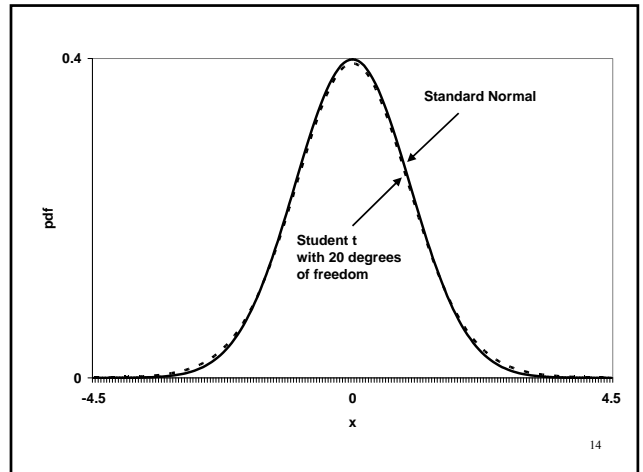
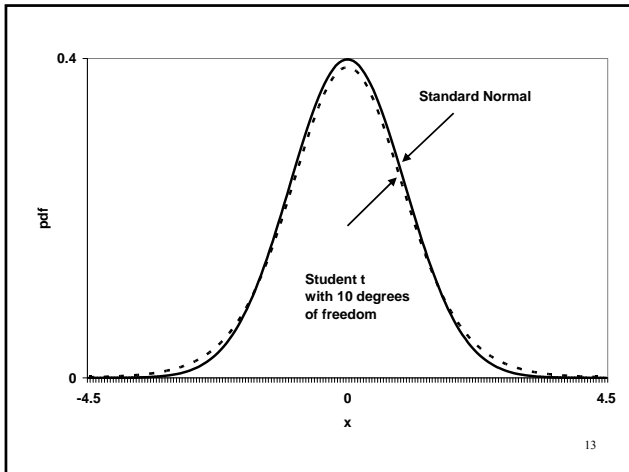
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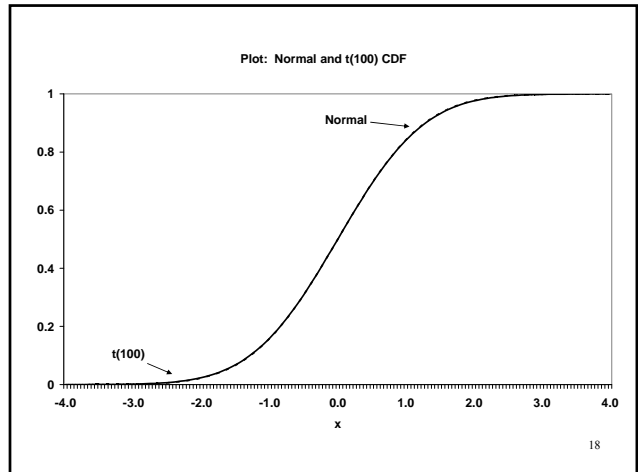
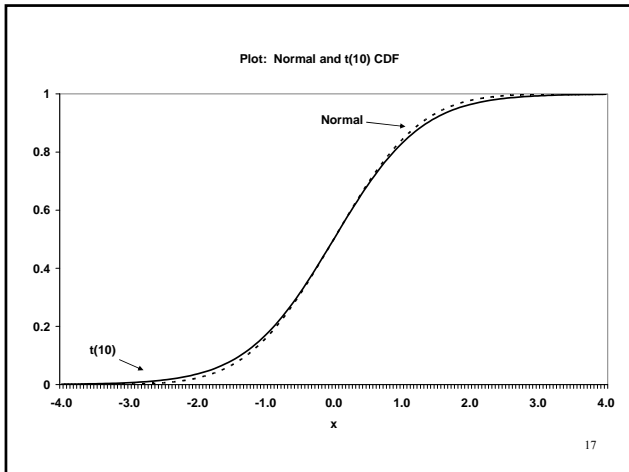


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Normality of ϵ

- $y_i = \beta_0 + x_{1i}\beta_1 + x_{2i}\beta_2 + \dots + x_{ki}\beta_k + \epsilon_i$
- There are n observations
- $k+1$ parameters to be estimated
- $n-k-1$ degrees of freedom
- Assume ϵ_i is normally distributed.
- What does that assumption buy us?

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$$y_i = \beta_0 + x_i\beta_1 + \epsilon_i$$

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2} = \beta_1 + \frac{\sum_{i=1}^n (x_i - \bar{x})\epsilon_i}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

$$= \beta_1 + \sum_{i=1}^n w_i \epsilon_i \quad \text{where} \quad w_i = \frac{(x_i - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

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- Note that $\hat{\beta}_1$ is a linear estimator, that is

$$\hat{\beta}_1 = \beta_1 + \sum_{i=1}^n w_i \varepsilon_i$$

- Note $\hat{\beta}_1$ is a linear function of the ε_i 's
- A linear function of normal variables is also normally distributed
- Since the ε_i 's are assumed to be normal...

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then $\hat{\beta}_1$ is normally distributed

$$\hat{\beta}_1 \sim \text{Normal}[\beta_1, V(\beta_1)]$$

$$E[\hat{\beta}_1] = \beta_1$$

$$V(\hat{\beta}_1) = \frac{\sigma_\varepsilon^2}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

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General case : $y_i = \beta_0 + x_{1i}\beta_1 + x_{2i}\beta_2 + \dots + x_{ki}\beta_k + \varepsilon_i$

then $\hat{\beta}_j$ is normally distributed

$$\hat{\beta}_j \sim \text{Normal}[\beta_j, V(\beta_j)]$$

$$E[\hat{\beta}_j] = \beta_j$$

$$V(\hat{\beta}_j) = \frac{\sigma_\varepsilon^2}{SST_j(1-R_j^2)}$$

where $SST_j = \sum_{i=1}^n (x_{ji} - \bar{x}_j)^2$ and $R_j^2 =$ the R^2 from the regression of x_j on all the other x 's

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because $\hat{\beta}_j$ is normally distributed, we could use the std. normal distribution for test of hypotheses IF WE KNEW σ_ε^2

$$\frac{\hat{\beta}_j - \beta_j}{\sqrt{V(\hat{\beta}_j)}} = \frac{\hat{\beta}_j - \beta_j}{\sqrt{\frac{\sigma_\varepsilon^2}{SST_j(1-R_j^2)}}} \sim N(0,1)$$

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Problem?

- σ_ε^2 is unknown and must be estimated
- Unbiased estimate is

$$\hat{\sigma}_\varepsilon^2 = \frac{\sum_{i=1}^n \hat{\varepsilon}_i^2}{n-k-1}$$

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$\hat{\varepsilon}_i = y_i - \hat{\beta}_0 - x_{1i}\hat{\beta}_1 - x_{2i}\hat{\beta}_2 - \dots - x_{ki}\hat{\beta}_k$
each $\hat{\beta}_j$ is normally distributed
therefore, $\hat{\varepsilon}_i$ a linear combination of
normally distributed variables

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$$\hat{\sigma}_\varepsilon^2 = \frac{\sum_{i=1}^n \hat{\varepsilon}_i^2}{n-k-1}$$

The numerator in the estimate looks something like a chi-squared. But because $\hat{\varepsilon}_i \sim N(0, \sigma_\varepsilon^2)$ (it does not have a var. of 1) it is not exactly in the correct form.

Technically, $(n-k-1)\hat{\sigma}_\varepsilon^2 / \sigma_\varepsilon^2 \sim \chi^2(n-k-1)$ ²⁷

- Because the n observations are already used to get k+1 parameters, there are only n-k-1 unique estimated errors
- Therefore, the degrees of freedom of the chi-squared distribution are n-k-1

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Recall that

$$\frac{\hat{\beta}_j - \beta_j}{\sqrt{V(\hat{\beta}_j)}} = \frac{\hat{\beta}_j - \beta_j}{\sqrt{\frac{\sigma_\varepsilon^2}{SST_j(1-R_j^2)}}} \sim N(0,1)$$

and $\frac{(n-k-1)\hat{\sigma}_\varepsilon^2}{\sigma_\varepsilon^2} \sim \chi^2(n-k-1)$

and $t = \frac{z}{\sqrt{\frac{W}{n}}} \sim t(n)$

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The theoretical variance for $\hat{\beta}_j$

$$V(\hat{\beta}_j) = \frac{\sigma_\varepsilon^2}{SST_j(1-R_j^2)}$$

The estimated variance is then

$$\hat{V}(\hat{\beta}_j) = \frac{\hat{\sigma}_\varepsilon^2}{SST_j(1-R_j^2)}$$

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Standard normal

$$\frac{\hat{\beta}_j - \beta_j}{\sqrt{V(\hat{\beta}_j)}} = \frac{N(0,1)}{\sqrt{\frac{\chi^2(n-k-1)}{n-k-1}}} \sim t(n-k-1)$$

Chi-squared

Degrees of freedom

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$$\frac{\frac{\hat{\beta}_j - \beta_j}{\sqrt{\frac{\sigma_\varepsilon^2}{SST_j(1-R_j^2)}}}}{\sqrt{\frac{\frac{(n-k-1)\hat{\sigma}_\varepsilon^2}{\sigma_\varepsilon^2}}{n-k-1}}} = \frac{\frac{\hat{\beta}_j - \beta_j}{\sqrt{\frac{\sigma_\varepsilon^2}{SST_j(1-R_j^2)}}}}{\sqrt{\frac{(n-k-1)\hat{\sigma}_\varepsilon^2}{(n-k-1)\sigma_\varepsilon^2}}} = \frac{\hat{\beta}_j - \beta_j}{\sqrt{\frac{\hat{\sigma}_\varepsilon^2}{SST_j(1-R_j^2)}}} \left(\frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2} \right)$$

$$= \frac{\hat{\beta}_j - \beta_j}{\sqrt{\frac{\hat{\sigma}_\varepsilon^2}{SST_j(1-R_j^2)}}} = \frac{\hat{\beta}_j - \beta_j}{\sqrt{\text{Est.Var}(\hat{\beta}_j)}} \sim t(n-k-1)$$

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Instead of working with

$$\frac{\hat{\beta}_j - \beta_j}{\sqrt{\frac{\hat{\sigma}_\varepsilon^2}{SST_j(1-R_j^2)}}} \sim N(0,1)$$

we use

$$\frac{\hat{\beta}_j - \beta_j}{\sqrt{\frac{\hat{\sigma}_\varepsilon^2}{SST_j(1-R_j^2)}}} \sim t(n-k-1)$$

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$se(\hat{\beta}_j)$ standard error of $\hat{\beta}_j$

$$se(\hat{\beta}_j) = \sqrt{\frac{\hat{\sigma}_\varepsilon^2}{SST_j(1-R_j^2)}}$$

$$\frac{\hat{\beta}_j - a}{se(\hat{\beta}_j)} \sim t(n-k-1)$$

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Testing Hypotheses about a Single Parameter: 2 tailed tests

- Basic model
- $y_i = \beta_0 + x_{1i}\beta_1 + x_{2i}\beta_2 + \dots + x_{ki}\beta_k + \varepsilon_i$
- Economic theory suggests a particular value of the parameter
- $H_0: \beta_j = a$
- $H_a: \beta_j \neq a$

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Two-tailed test

- These are called two tail tests because falsification of the null hypothesis can be due to either large + or - values (in absolute value)
- Therefore, we use both "tails" of the underlying t-distribution

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- The distribution for $\hat{\beta}_j$

$$\frac{\hat{\beta}_j - a}{se(\hat{\beta}_j)} \sim t(n - k - 1)$$

- Given the hypothesis is true, we can replace “a” for β_j

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$$\hat{t} = \frac{\hat{\beta}_j - a}{se(\hat{\beta}_j)} \sim t(n - k - 1)$$

- If the hypothesis is true, the constructed test statistic should be centered on zero. How “far” from zero does it have to be to reject the null?

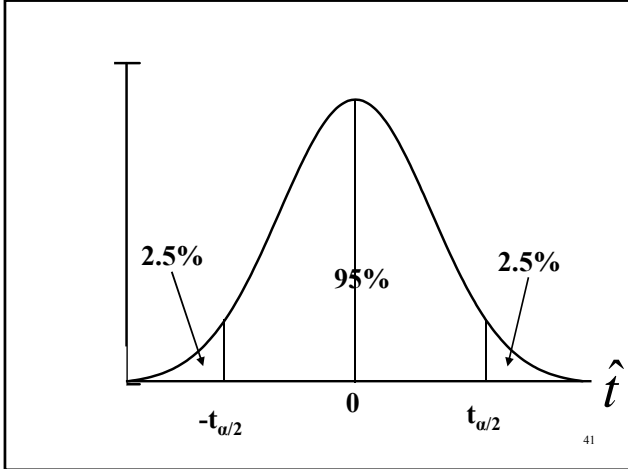
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- Need to set the “confidence level” of the test.
 - Usually 95%
- Let 1-confidence level = α
 - With 95% confidence level, $\alpha = 0.05$
- α is the probability you reject the null when it is in fact true ...return to this later

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- $t_{\alpha/2}(\text{dof})$ be the cut-off from a t-distribution with dof degrees of freedom where only $\alpha/2$ percent of the distribution lies above
- Given symmetry, $\alpha/2$ percent lies below $-t_{\alpha/2}(\text{dof})$

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- If we were to draw \hat{t} at random, 95% of the time it would be between $(-t_{\alpha/2}, t_{\alpha/2})$
- Therefore, if the hypothesized value of β_j is true, there is a 95% chance \hat{t} will be between $(-t_{\alpha/2}, t_{\alpha/2})$

Decision Rule

$$\hat{t} = \frac{\hat{\beta}_j - a}{se(\hat{\beta}_j)} \sim t(n - k - 1)$$

if $|\hat{t}| \geq t_{\alpha/2}(n - k - 1)$ reject null
 if $|\hat{t}| < t_{\alpha/2}(n - k - 1)$ cannot reject null

Most basic test

- $y_i = \beta_0 + x_{1i}\beta_1 + x_{2i}\beta_2 + \dots + x_{ki}\beta_k + \epsilon_i$
- $H_0: \beta_j = 0$
- $H_a: \beta_j \neq 0$
- Is the parameter estimate statistically distinguishable from zero?

Baseball example

- Regress attendance on wins – do winning teams attract more fans
- Data on 30 teams, 2 parameters, $DOF=n-2=28$
- Look at table in the back of the book for critical value of t
 - Vertical axis is DOF
 - Horizontal axis is the value of α

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Significance Level

		Significance Level					P-value for two tailed tests
		0.100	0.050	0.025	0.010	0.005	
one-tailed tests	two-tailed tests	0.200	0.100	0.050	0.020	0.010	
Degrees of freedom	1	3.078	6.314	12.706	31.821	63.657	
	2	1.886	2.920	4.303	6.965	9.925	
	3	1.638	2.353	3.182	4.541	5.841	
	4	1.533	2.132	2.776	3.747	4.604	
	5	1.476	2.015	2.571	3.365	4.032	
	15	1.341	1.753	2.131	2.602	2.947	
	16	1.337	1.746	2.120	2.583	2.921	
	17	1.333	1.740	2.110	2.567	2.898	
	18	1.330	1.734	2.101	2.552	2.878	
	19	1.328	1.729	2.093	2.539	2.861	
	20	1.325	1.725	2.086	2.528	2.845	
	21	1.323	1.721	2.080	2.518	2.831	
	22	1.321	1.717	2.074	2.508	2.819	
	23	1.319	1.714	2.069	2.500	2.807	
	24	1.318	1.711	2.064	2.492	2.797	
	25	1.316	1.708	2.060	2.485	2.787	
	26	1.315	1.706	2.056	2.479	2.779	
	27	1.314	1.703	2.052	2.473	2.771	
	28	1.313	1.701	2.048	2.467	2.763	
	29	1.311	1.699	2.045	2.462	2.756	
	30	1.310	1.697	2.042	2.457	2.750	

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```

* run simple regression
reg attendance wins

Source |      SS      df      MS      Number of obs =      30
-----+-----+-----+-----+-----+-----
Model |  606784507      1  606784507      F( 1, 28) =      8.89
Residual | 1.9110e+09     28  68249360.1      Prob > F      =  0.0059
-----+-----+-----+-----+-----
Total | 2.5178e+09     29  86819537.6      R-squared      =  0.2410
                                           Adj R-squared  =  0.2139
                                           Root MSE     =  8261.3

attendance |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----+-----+-----+-----+-----
wins |  310.0473   103.9825     2.98  0.006   97.04894   523.0457
_cons | 3095.14    8539.507     0.36  0.720  -14397.25  20587.53
    
```

$$\hat{t} = \frac{\hat{\beta}_j - a}{se(\hat{\beta}_j)} = \frac{310.05 - 0}{103.98} = 2.98$$

$$|\hat{t}| = 2.98 > t_{\alpha/2}(n - k - 1) = 2.048 \quad \therefore \text{reject null}$$

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Statistical significance

- When we reject the null hypothesis that $H_0: \beta_j=0$, we say that a variable is “statistically significant”
- Which is short hand for saying the variable is statistically distinguishable from 0
- Statistically insignificant variables are those that we cannot reject the null $H_0: \beta_j=0$

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College GPA example

- Data on 141 students
- 2 continuous variables:
 - HS GPA
 - ACT Score
- One intercept
- $DOF = n-k-1 = 141-3 = 138$
- On the table, there is no 138, just find the closest one

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5	1.476	2.015	2.571	3.365	4.032
15	1.341	1.753	2.131	2.602	2.947
35	1.306	1.690	2.030	2.438	2.724
36	1.306	1.688	2.028	2.434	2.719
37	1.305	1.687	2.026	2.431	2.715
38	1.304	1.686	2.024	2.429	2.712
39	1.304	1.685	2.023	2.426	2.708
40	1.303	1.684	2.021	2.423	2.704
60	1.296	1.671	2.000	2.390	2.660
90	1.291	1.662	1.987	2.368	2.632
120	1.289	1.658	1.980	2.358	2.617
infinity	1.282	1.645	1.960	2.326	2.576

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```

* run multivariate regression
. reg college_gpa act hs_gpa

Source |         SS          df           MS              Number of obs =   141
-----|-----
Model |  3.42365506         2   1.71182753              F( 2, 138) =  14.78
Residual | 15.9824444         138   .115814814              Prob > F      =  0.0000
Total   | 19.4060994         140   .138614996              R-squared     =  0.1764
                                           Adj R-squared =  0.1645
                                           Root MSE    =  .34032
    
```

college_gpa	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
act	-.009426	.0107772	0.87	0.383	-.0118838 .0307358
hs_gpa	.4534539	.0958129	4.73	0.000	.2640047 .6429071
_cons	1.286328	.3408221	3.77	0.000	.612419 1.960237

$$\hat{t}_{act} = 0.87$$

$|\hat{t}_{act}| < 1.98 \therefore \text{cannot reject null}$

$$\hat{t}_{hs_gpa} = 4.73$$

$|\hat{t}_{hs_gpa}| \geq 1.98 \therefore \text{reject null}$

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Confidence intervals

- The CI represent the 95% most likely values of the parameter β_j
- If the hypothesized value “a” ($H_0: \beta_j=a$) is not part of the confidence interval, it is not a likely value and we reject the null
- If interval contains “a” we cannot reject null
- The t-test and CI should provide the same decision – if not, you did something wrong

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Confidence intervals

if the null is true, then

$$-t_{\alpha/2}(n-k-1) \leq \frac{\hat{\beta}_j - a}{se(\hat{\beta}_j)} \leq t_{\alpha/2}(n-k-1)$$

which means that

$$\hat{\beta}_j - se(\hat{\beta}_j)t_{\alpha/2}(n-k-1) \leq a \leq \hat{\beta}_j + se(\hat{\beta}_j)t_{\alpha/2}(n-k-1)$$

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Confidence interval

$$\hat{\beta}_j \pm se(\hat{\beta}_j)t_{\alpha/2}(n-k-1)$$

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```

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				R-squared =	0.2410	
				Adj R-squared =	0.2139	
				Root MSE =	8261.3	
Total	2.5178e+09	29	86819537.6			

attendance	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
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confidence int.

$$\hat{\beta}_j \pm t_{\alpha/2}(n-k-1)se(\hat{\beta}_j)$$

$$310.05 \pm 2.0484(103.98)$$

$$[97.04, 523.05] \therefore \text{reject null } \beta_j = 0$$

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two-tailed tests		0.200	0.100	0.050	0.020	0.010
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reg college_gpa act hs_gpa
```

Source	SS	df	MS	Number of obs = 141		
Model	3.42365506	2	1.71182753	F(2, 138) = 14.78		
Residual	15.9824444	138	.115814814	Prob > F = 0.0000		
-----				R-squared = 0.1764		
-----				Adj R-squared = 0.1645		
-----				Root MSE = .34032		

college_gpa	act	hs_gpa	_cons	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
	act			.009426	.0107772	0.87	0.383	-.0118838 .0307358
		hs_gpa		-.4534559	.0958129	-4.73	0.000	.2640047 .6429071
			_cons	1.286328	.3408221	3.77	0.000	.612419 1.960237

confidence int.
 $\hat{\beta}_j \pm t_{\alpha/2}(n-k-1)se(\hat{\beta}_j)$
 $0.0094 \pm 1.98(0.01078)$
 $[-0.0119, 0.0307] \therefore \text{cannot reject null } \beta_j = 0$

Problem Set 3

- Regress $\ln(q)$ on $\ln(p)$
- Test whether the cigarette demand elasticity is an “elastic” response, that is $\zeta_d = -1$
- 20 years worth of data, 51 states = 1020
- DOF = $n-2 = 1018$

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		Significance Level				
one-tailed tests		0.100	0.050	0.025	0.010	0.005
two-tailed tests		0.200	0.100	0.050	0.020	0.010
Degrees of freedom	1	3.078	6.314	12.706	31.821	63.657
	2	1.886	2.920	4.303	6.965	9.925
	3	1.638	2.353	3.182	4.541	5.841
	4	1.533	2.132	2.776	3.747	4.604
	5	1.476	2.015	2.571	3.365	4.032
	25	1.316	1.708	2.060	2.485	2.787
	50	1.299	1.676	2.009	2.403	2.678
	100	1.290	1.660	1.984	2.364	2.626
	250	1.285	1.651	1.969	2.341	2.596
	500	1.283	1.648	1.965	2.334	2.586
	750	1.283	1.647	1.963	2.331	2.582
	1000	1.282	1.646	1.962	2.330	2.581
	1018	1.282	1.646	1.962	2.330	2.581
	infinity	1.282	1.645	1.960	2.326	2.576

Just looking at confidence interval, we can reject the null

Source	SS	df	MS	Number of obs = 1020	
Model	36.0468802	1	36.0468802	F(1, 1018) =	873.39
Residual	42.0153163	1018	.041272413	Prob > F =	0.0000
Total	78.0621965	1019	.07660667	R-squared =	0.4618
				Adj R-squared =	0.4612
				Root MSE =	.20316

ln_q	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
ln_p	-.8076941	.0273302	-29.55	0.000	<u>-.8613241 - .7540641</u>
_cons	8.834473	.1423221	62.07	0.000	8.555195 9.113751

$$\ln(q_i) = \beta_0 + \ln(p_i)\beta_1 + \varepsilon_i \quad \hat{t} = \frac{\hat{\beta}_1 - a}{se(\hat{\beta}_1)} = \frac{-0.808 - -1}{0.0273} = \frac{0.192}{0.0273} = 7.03$$

H₀: β₁ = -1

$$t_{\alpha/2}(dof) = t_{0.025}(1018) = 1.96$$

$$|\hat{t}| > 1.96 \quad \therefore \text{reject null}$$

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P-value

- Alternative way of characterizing the data contained in the t-test
- Given that the null is true, the **p-value** is probability of obtaining a result at least as extreme as the one that was actually observed
- Calculate \hat{t}
- In the two tailed test, the p-value is then

$$p\text{-value} = \Pr(t \leq -|\hat{t}|) + \Pr(t > |\hat{t}|)$$

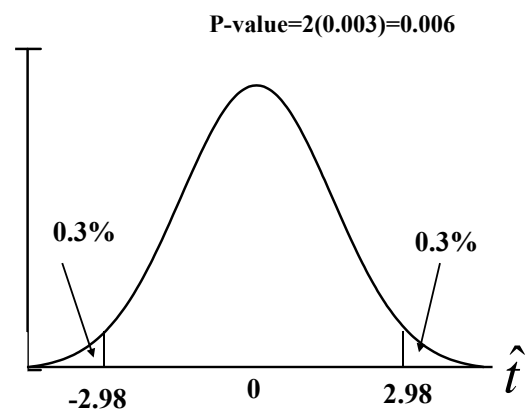
62

* run simple regression
reg attendance wins

Source	SS	df	MS	Number of obs = 30	
Model	606784507	1	606784507	F(1, 28) =	8.89
Residual	1.9110e+09	28	68249360.1	Prob > F =	0.0059
Total	2.5178e+09	29	86819537.6	R-squared =	0.2410
				Adj R-squared =	0.2139
				Root MSE =	8261.3

attendance	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
wins	310.0473	103.9825	2.98	0.006	97.04894 523.0457
_cons	3095.14	8539.507	0.36	0.720	-14397.25 20587.53

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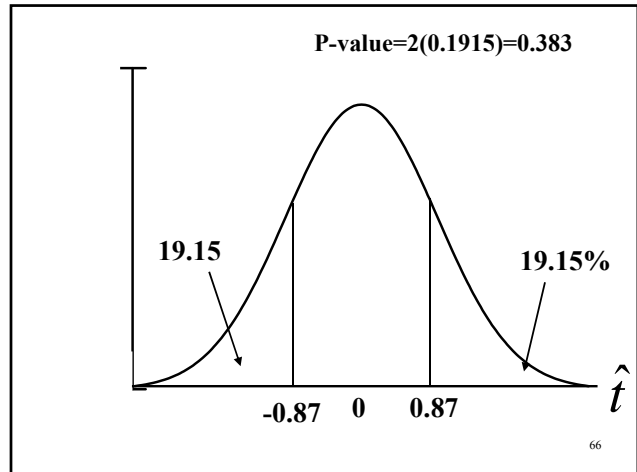
64


```
* run multivariate regression
. reg college_gpa act hs_gpa
```

Source	SS	df	MS			
Model	3.42365506	2	1.71182753	Number of obs =	141	
Residual	15.9824444	138	.115814814	F(2, 138) =	14.78	
Total	19.4060994	140	.138614996	Prob > F =	0.0000	
				R-squared =	0.1764	
				Adj R-squared =	0.1645	
				Root MSE =	.34032	

college_gpa	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
act	.009426	.0107772	0.87	0.383	-.0118838 .0307358
hs_gpa	.4534559	.0958129	4.73	0.000	.2640047 .6429071
_cons	1.286328	.3408221	3.77	0.000	.612419 1.960237

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- A small p-value gives you confidence that you can reject the null hypothesis – you would not get a value this large (in absolute value) at random, therefore, the H_0 must be false

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- ### Note
- Using p-value, t-test, confidence interval are three ways to get the same results
 - The decision rule (reject or not reject) should not vary across test methods
 - Good check on your work --

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Errors in Prediction

- Statistical tests can be used as tests of theoretical hypothesis
 - Do demand curves slope down?
 - Do wages increase w/more education?
- These are only statistical tests – they ask, in a probabilistic sense, what is the likely state of the world
- Consider $H_0: \beta_j=0$
- Suppose the t-test is small, so you *cannot reject* the null hypothesis. There is always a chance that you are wrong.

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Example 1: New Drug

- Reduces deaths from stroke by 10%. However a clinical trial cannot reject the null hypothesis that there is no effect
- t-statistic on the active ingredient is 1.12
- Cannot reject null that $\beta_j=0$

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Two possible situations

- Drug does not work and your test is correct
- Drug does work, but the statistical model did not have enough power to detect a statistically significant impact

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Type I and II Errors

		Decision	
		Cannot reject H_0	Reject H_0
True State	H_0 true	Correct decision	Type I error Reject true hypothesis
	H_0 false	Type II error Accept false hypothesis	Correct decision

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- Type I – false positive
- Type II – false negative
- In regression, $H_0: \beta_j=0$
 - Type I – you reject that $\beta_j=0$ when it equals 0
 - Type II – you cannot reject $\beta_j=0$ when $\beta_j \neq 0$

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What is the probability you will make a “wrong” decision

- Type I error – reject null when it is in fact true
 - $H_0: \beta_j=0$
 - Get large t-statistic so reject null
- There is a chance that, by accident, you will get a large t-stat
- What is that chance? $1 - \text{confidence level} = \alpha$ so α is the probability

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- Type II errors: Do not reject null when it is in fact false
 - $H_0: \beta_j=0$
 - Get small t-statistic so do not reject null
- What is the probability this will happen?
 - The type II error rate (false negative) labeled β
 - $1 - \beta$ called the “power of the test”
 - Factors that increase power
 - Increase sample size
 - Increase variation in X's

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- Depending on the problem, need to balance the probabilities of Type I and II errors
- If concerned about Type I errors, so you increase the size of the confidence interval – Increase the chance of Type II error

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Example: Criminal Court

- Consider criminal court:
 - H_0 : not guilty
 - Job of jury – decide guilty or not guilty
 - Type I error – reject true hypothesis
 - convict an innocent man
 - Type II error – accept a false hypothesis
 - let guilty man go free
- Decision rule: guilt beyond a reasonable doubt
- Requires low p-value, high confidence level (99.99% confidence interval) to convict – minimize Type I

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Example: Mammography

- Low level radiation exam to detect breast exam
- H_0 : no breast cancer
 - Type I error – False positive – find a cancer growth but it does not exist
 - Type II error – False negative – fails to detect a growth
- What do you minimize?

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- Consider the doctor's liability –
 - Suppose a Type II error happens – failed to find tumor -- patient dies – gets sued for malpractice
 - Suppose a Type I error – detect tumor, perform surgery when none was needed –
- For the doctor, what type of error has more “downside” risk?

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Changing confidence level

- 95% CI is “industry standard”
 - Only 5% error rate
- But, maybe want to decrease Type I error rate
 - Decrease false positives
 - Increase confidence level to 99%
 - Maybe you really need to be sure something causes cancer before you ban the substance

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- In contrast, you might want to decrease chance of Type II error
 - Reduce the size of the confidence interval
 - Maybe do not require as definitive evidence before you let on the market a new drug to treat in incurable disease

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In STATA

- `reg y x1 x2 x3, level(#)`
- The # is a number from 10 to 99.99
 - the top number has a low Type I (.01%)
 - very high Type II error rare

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Test score data from CA

- 420 schools
- 6 graders given math/reading exams
- Outcome is average score on both exams
- Four covariates
 - Student/teacher ratio
 - Average family income (in thousands of \$)
 - % ESL
 - % on free and reduced lunches

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```

. desc average_score student_teacher avg_income esl_pct meal_pct

variable name      storage  display  value  variable label
                  type    format   label
-----
average_score      float    %9.0g    average score (math+read) std
                  test
student_teacher    float    %9.0g    student/teacher ratio
avg_income          float    %9.0g    average family income
esl_pct            float    %9.0g    pct student with english
                  second language
meal_pct           float    %9.0g    % kids on free/reduced prices
                  meals

. sum average_score student_teacher avg_income esl_pct meal_pct

Variable | Obs    Mean    Std. Dev.  Min    Max
-----|-----
average_sc-e | 420    654.1565  19.05335   605.55  706.75
student_te-r | 420    19.64043  1.891812   14      25.8
avg_income    | 420    15.31659  7.22589    5.335   55.328
esl_pct       | 420    15.76816  18.28593   0       85.53972
meal_pct      | 420    44.70524  27.12338   0       100

```

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```

. * run mv regression with 4 x's
. reg average_score student_teacher avg_income esl_pct meal_pct

```

Source	SS	df	MS	Number of obs = 420		
Model	122493.527	4	30623.3818	F(4, 415) = 429.12		
Residual	29616.0666	415	71.3640159	Prob > F = 0.0000		
Total	152109.594	419	363.030056	R-squared = 0.8053		
				Adj R-squared = 0.8034		
				Root MSE = 8.4477		

average_sc-e	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
student_te-r	-.5603892	.2286116	-2.45	0.015	-1.00977 - .1110081
avg_income	.674984	.083331	8.10	0.000	.5111805 .8387875
esl_pct	-.1943282	.0313796	-6.19	0.000	-.256011 - .1326454
meal_pct	-.3963661	.0274084	-14.46	0.000	-.4502427 - .3424895
_cons	675.6082	5.308856	127.26	0.000	665.1726 686.0438

Notice the t-statistic on Student/teacher ratio is 2.45
At 95% level, can reject null $\beta = 0$. Notice the P-value is 0.015, so a 99% CI would not reject null

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		Significance Level				
one-tailed tests		0.100	0.050	0.025	0.010	0.005
two-tailed tests		0.200	0.100	0.050	0.020	0.010
Degrees of freedom	1	3.078	6.314	12.706	31.821	63.657
	2	1.886	2.920	4.303	6.965	9.925
	3	1.638	2.353	3.182	4.541	5.841
	4	1.533	2.132	2.776	3.747	4.604
	5	1.476	2.015	2.571	3.365	4.032
	25	1.316	1.708	2.060	2.485	2.787
	50	1.299	1.676	2.009	2.403	2.678
	100	1.290	1.660	1.984	2.364	2.626
	120	1.289	1.658	1.980	2.358	2.617
	200	1.286	1.653	1.972	2.345	2.601
	300	1.284	1.650	1.968	2.339	2.592
400	1.284	1.649	1.966	2.336	2.588	
415	1.284	1.649	1.966	2.335	2.588	
infinity	1.282	1.645	1.960	2.326	2.576	

To change CI, use this option

```

. * run the same regression but ask for a 99% confidence level
. reg average_score student_teacher avg_income esl_pct meal_pct, level(99)

```

Source	SS	df	MS	Number of obs = 420		
Model	122493.527	4	30623.3818	F(4, 415) = 429.12		
Residual	29616.0666	415	71.3640159	Prob > F = 0.0000		
Total	152109.594	419	363.030056	R-squared = 0.8053		
				Adj R-squared = 0.8034		
				Root MSE = 8.4477		

average_sc-e	Coef.	Std. Err.	t	P> t	[99% Conf. Interval]
student_te-r	-.5603892	.2286116	-2.45	0.015	-1.151974 .0311954
avg_income	.674984	.083331	8.10	0.000	.4593461 .8906219
esl_pct	-.1943282	.0313796	-6.19	0.000	-.2755301 - .1131263
meal_pct	-.3963661	.0274084	-14.46	0.000	-.4672916 - .3254406
_cons	675.6082	5.308856	127.26	0.000	661.8703 689.3461

confidence int.

$$\hat{\beta}_j \pm t_{\alpha/2}(n-k-1)se(\hat{\beta}_j)$$

$$0.5604 \pm 2.588(0.2286) = [-1.152, 0.031]$$

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