STA302/STA1001, Week 3

Mark Ebden, 21–26 September 2017

With grateful acknowledgment to Alison Gibbs and Becky Lin

Today's class

- The Confidence Interval in Linear Regression
- Hypothesis testing on β_0 and β_1
- Regression Analysis of Variance
- Reference: Simon Sheather §§2.2 – 2.5

Computing Labs with R installed

Robarts has a Computer Lab open whenever the library itself is open:

- `https://mdl.library.utoronto.ca/technology/computer-lab`
- Monday to Friday 8:30 am to 11 pm
- Saturday 9 am - 10 pm
- Sunday 10 am - 10 pm

There are also four IIT (Information & Instructional Technology) labs:

- In Sidney Smith Hall, Carr Hall, and in Ramsay Wright
- Need Help with an IIT lab? Phone: 416-946-HELP (4357)
- Email: `iit@artsci.utoronto.ca`
- Walk-in: Come to Sidney Smith Room 572 (IIT Office), Monday to Friday, 8:45 am - 5:00 pm

More about the IIT Computer Labs

The four are:

- Sidney Smith Hall room 561 (lower level) (49 seats) - 100 St. George Street: 8:45 am to 7 pm
- Carr Hall room 325 (3rd floor) (30 seats) - 100 St. Joseph Street: 8:45 am to 9 pm
- Ramsay Wright room 107 (20 seats) - 25 Harbord Street: 8:45 am to 9 pm
- Ramsay Wright room 109 (24 seats) - 25 Harbord Street: 8:45 am to 9 pm

Before dropping in, click the links at left here to ensure the room hasn't been booked: `http://lab.chass.utoronto.ca/schedules.php`

More about the IIT Computer Labs

Logging in:

- You must use a valid UTORid and password to log in to lab computers
- If you have trouble logging in, please verify your UTORid credentials at `https://www.utorid.utoronto.ca` (click on the “verify” link under the yellow “Problems with your UTORid?” heading). If your UTORid username and password do not work, reset your password on this page.
- For more help, contact the IIT labs, or reach the Information Commons helpdesk at 416-978-HELP (4357) or `help.desk@utoronto.ca`

More about the IIT Computer Labs

Printing:

- Printing is available in the Sidney Smith and Ramsay Wright labs, but not Carr Hall
- You must have a TCard with sufficient value stored on it. A card reader attached to the print release station will debit the print job cost from your TCard at the time of printing

Saving Data:

- Data is not saved on the lab computers
- Back-up your data frequently, and ensure you have an appropriate storage and/or back-up method for your files (e.g. use a USB key or email materials to yourself)

A note about correlation

In Week 2, we introduced the assumption that the e_i's are uncorrelated. This means that:

pearson correlation coefficient

$$\rho_{ij} = \frac{\mathrm{cov}(e_i, e_j)}{\sigma_i \sigma_j} = 0 \quad \forall\, i \neq j$$

where ρ_{ij} indicates the linear correlation between any two of the e's

Lack of correlation is a gentler assumption than independence:

- Two independent random variables will have correlation 0, but not necessarily vice versa
- Consider for example $X \sim \mathrm{Unif}(-1, 1)$ and $Y = X^2$, which are dependent but $\mathrm{cov}(X, Y) = \mathbb{E}(X^3) = 0$

Towards a Confidence Interval

For a chosen value of x^*,

$$\hat{y}^* = \hat{\beta}_0 + \hat{\beta}_1 x^*$$

Because $\hat{\beta}_0$ and $\hat{\beta}_1$ are unbiased estimates,

$$\mathbb{E}(\hat{y}^*) = \beta_0 + \beta_1 x^*$$

And, using our equations from Week 2,

$$\begin{aligned}
\mathrm{var}(\hat{y}^*) &= \mathrm{var}(\hat{\beta}_0) + \ (x^*)^2 \mathrm{var}(\hat{\beta}_1) \ + \ 2x^* \mathrm{cov}\left(\hat{\beta}_0, \hat{\beta}_1\right) \\
&= \sigma^2 \left[\frac{1}{n} + \frac{\bar{x}^2}{S_{xx}}\right] + \ \frac{(x^*)^2 \sigma^2}{S_{xx}} \ - \ \frac{2x^* \sigma^2 \bar{x}}{S_{xx}} \\
&= \sigma^2 \left[\frac{1}{n} + \frac{(x^* - \bar{x})^2}{S_{xx}}\right]
\end{aligned}$$

sigma^2 is unknown from data, usually have to estimate

Towards a Confidence Interval

Now bringing in our assumption from Tuesday that the errors are normally distributed:

$$\hat{y}^* \sim \mathcal{N}\left(\beta_0 + \beta_1 x^*,\, \sigma^2 \left[\frac{1}{n} + \frac{(x^* - \bar{x})^2}{S_{xx}}\right]\right)$$

Equivalently we can write this as

$$Z = \frac{\hat{y}^* - (\beta_0 + \beta_1 x^*)}{\sigma\sqrt{\frac{1}{n} + \frac{(x^* - \bar{x})^2}{S_{xx}}}} \sim \mathcal{N}(0, 1)$$

standardization

Towards a Confidence Interval

We don't generally know σ^2, but can estimate using the mean square error, S^2, as in question 3 from last week. This changes our Z score into a T score:

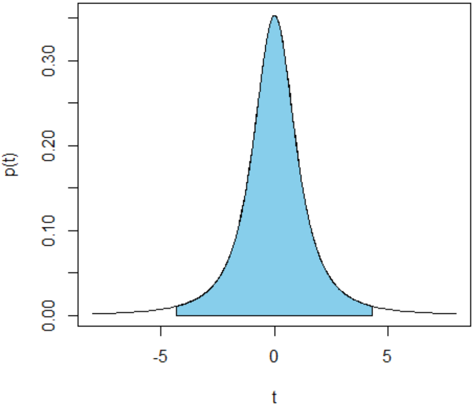
$$T = \frac{\hat{y}^* - (\beta_0 + \beta_1 x^*)}{S\sqrt{\frac{1}{n} + \frac{(x^* - \bar{x})^2}{S_{xx}}}} \;\sim\; t_{n-2}$$

This distribution tells us that for a given value of x^*:

- The difference between $\hat{y}^*$ and the population regression line's ordinate, $\mathbb{E}(Y|X = x^*) = \beta_0 + \beta_1 x^*$, follows a (scaled) t_{n-2} distribution

A Confidence Interval

What upper- and lower bounds on $\hat{y}^*$ can be expected to encompass the population regression line, i.e. encompass the true $\mathbb{E}(Y^*)$, 95% of the time?



The answer is called a 95% confidence interval.

R code to shade a graph

```
c1 = qt(0.025,2) # Left bound of shaded region
c2 = qt(0.975,2)
x0 = 8 # Highest t-score to plot
myseq = seq(c1, c2, 0.01)
cx <- c(c1,myseq,c2) # vector of x-points to outline shaded region
cy <- c(0,dt(myseq,2),0)
curve(dt(x,2),xlim=c(-x0,x0),xlab='t',ylab='p(t)')
polygon(cx,cy,col='skyblue') # connect the dots
```

You don't need to know the `curve` and `polygon` commands

Quantiles of t_{n-2}

We'll represent the quantile function, $F^{-1}(p)$, of the t distribution by $t(1-p,\nu)$, where p is the cumulative probability and ν is the number of degrees of freedom.

For our 95% confidence interval:

- In the lower bound we'll set $p = \alpha/2 = 0.05/2$
- In the upper bound we'll set $p = 1 - \alpha/2 = 0.975$

Thus we're interested in two cases: $t(\alpha/2, n-2)$ and $t(1-\alpha/2, n-2)$.

Equivalently, because the t distribution is symmetric, and because $\alpha = 0.05$, we're interested in $\pm\, t(0.025, n-2)$.

Specifying the Confidence Interval

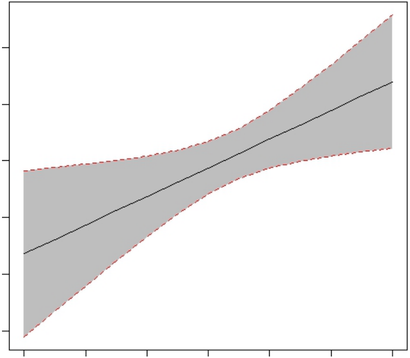
From our expression for T (slide 10), we see that the two limits of the confidence interval are given by:

$$\hat{y}^* \pm t(0.025, n-2)\, S \sqrt{\frac{1}{n} + \frac{(x^* - \bar{x})^2}{S_{xx}}}$$

or equivalently:

$$\left(\hat{\beta}_0 + \hat{\beta}_1 x^*\right) \pm t(0.025, n-2)\, S \sqrt{\frac{1}{n} + \frac{(x^* - \bar{x})^2}{S_{xx}}}$$

Plot of Pointwise Confidence intervals



Exercise: Produce this kind of plot for a small data set:

$$\{(2,1),(4,3),(6,6)\}$$

Don't worry about shading, but you should know how to plot the three lines: upper, mean, lower.

What about Confidence Intervals for $\hat{\beta}_0$ and $\hat{\beta}_1$?

Developing on question #3

S^2 = MSE = RSS/(n-2)

Our estimator of σ^2 in question #3 from last week, S^2, is the Mean Square Error (MSE).

Our means and variances are expressed in terms of σ, which is unknown, hence the importance of question #3.

For example, the variance of $\hat{\beta}_1$ was found to be

$$\mathrm{var}(\hat{\beta}_1) = \frac{\sigma^2}{S_{xx}}$$

However, we use S in place of σ to get:

$$\widehat{\mathrm{var}}\left(\hat{\beta}_1\right) = \frac{S^2}{S_{xx}}$$

estimator of (variance of an estimator)

Standard error

The square root of this is known as the *standard error* (the estimate of the standard deviation of a parameter) in regression. So,

standard deviation of an estimator

$$\text{se}\left(\hat{\beta}_1\right) = \sqrt{\frac{S^2}{S_{xx}}}$$

and of course

$$\text{se}\left(\hat{\beta}_0\right) = \sqrt{S^2\left(\frac{1}{n} + \frac{\bar{x}^2}{S_{xx}}\right)}$$

You're already used to more simply referring to standard error as the standard deviation of a sampling distribution.

Recap of our guesses about β_1

We've shown how to estimate the mean and variance of $\hat{\beta}_1$.

Then, following the same kind of logic we used in the confidence intervals for $\hat{y}^*$, we can show that:

$$T = \frac{\hat{\beta}_1 - \beta_1}{\text{se}\left(\hat{\beta}_1\right)} \sim t_{n-2}$$

And thus the bounds of the confidence interval are:

$$\hat{\beta}_1 \pm t(0.025, n-2)\, \text{se}(\hat{\beta}_1)$$

Similarly, for $\hat{\beta}_0$:

$$\hat{\beta}_0 \pm t(0.025, n-2)\, \text{se}(\hat{\beta}_0)$$

More than one conception of standard error

1. A familiar way to find standard error:

- Collect n observations of some phenomenon
- Measure the sample variance, s^2
- $\text{se} = \sigma/\sqrt{n}$ and $\widehat{\text{se}} = s/\sqrt{n}$
- Some authors (but not Rice for example) say directly: $\text{se} = s/\sqrt{n}$

2. In regression analysis:

- Estimate the variance of the ith predictor estimate, i.e. $\widehat{\text{var}\left(\hat{\beta}_i\right)}$
- $\text{se} = \sqrt{\widehat{\text{var}\left(\hat{\beta}_i\right)}}$
- i.e. we're concerned with the s.d. of a parameter that stemmed from linear regression, not from a sampling distribution
- If you don't like conflating two terms, you may refer to one as the "s.e. of the regression"

Today's class

- The Confidence Interval in Linear Regression
- **Hypothesis testing on β_0 and β_1**
- Regression Analysis of Variance
- Reference: Simon Sheather §§2.2 – 2.5

Suppose we want to test whether β_1 is likely to be a particular value, β_1^0. For example, perhaps $\beta_1^0 = 0$.

This is an example of the kind of problem on which we can apply a *hypothesis test*

Hypothesis testing

We establish a pair of hypotheses:

- H_0 (null hypothesis): $\beta_1 = \beta_1^0$
- H_1 or H_a (alternative hypothesis): $\beta_1 \neq \beta_1^0$

A statistical hypothesis evaluates the compatibility of H0 with the data. We can evaluate H_0 by answering:

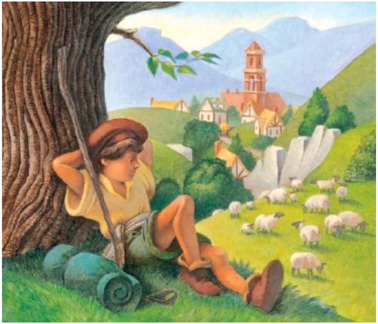
- Is our estimated $\hat{\beta}_1$ plausible/probable if H_0 is true?
- Is the difference between β_1^0 and our estimated $\hat{\beta}_1$ *large* compared to experimental noise?

The outcome here is binary:

- Reject H_0 (accept H_1), or don't reject H_0 (some authors would say "accept H_0")
- Therefore, whenever we run a hypothesis test, we run the risk of drawing one of two kinds of false conclusion (next slide)

What can go wrong with statistical hypothesis testing?

Decision	H_0 True	H_0 False
Do not reject H_0	Correct	Type II error
Reject H_0	Type I error	Correct power



Error rates

The type I error rate is defined as:

$$\alpha = P(\text{Reject } H_0 | H_0 \text{ is true})$$

The type II error rate is defined as:

$$\beta = P(\text{Don't reject } H_0 | H_1 \text{ is true})$$

It's perhaps unfortunate for us that this represents another β, by coincidence. Not to be confused with our familiar β_0 or β_1 in STA302.

Statistical hypotheses and power

Power (a.k.a. sensitivity) is defined as:

$$\begin{aligned} \text{power} &= 1 - \beta \\ &= 1 - P(\text{Don't reject } H_0 | H_1 \text{ is true}) \\ &= P(\text{Reject } H_0 | H_1 \text{ is true}) \end{aligned}$$

The probability that a fixed-level α test will reject H_0 when a particular alternative value of the parameter is true is called the *power* of the test to detect that alternative.

How to decide which hypothesis is more likely

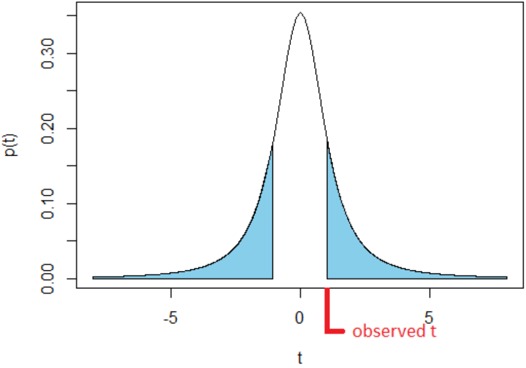
- You've encountered several statistics which measure central tendency, variability, etc, in an effort to describe/summarize some data
- When a statistic is used in hypothesis testing, it's known as the *test statistic*
- And when this statistic follows a t-distribution under the null hypothesis, our hypothesis test is an example of a t-**test**, a.k.a. Student's t-test
- These should usually be two-sided (we prepare for the test statistic's being abnormally high or low) but you do see one-sided tests as well (when the analyst says they have good reason to only check for one or the other of the high/low cases)

Key point: Temporarily assume H_0 is true. Then t_{observed} would be an observation from a t_{n-2} distribution. Is the t_{observed} you saw actually a reasonable-looking sample from that distribution?

The Student's t-test

This is one kind of testing that reports a "p-value". Based on the density function $p(t)$, and the observed statistic t_{observed}:

$$
\begin{aligned}
p\text{-value} &= P\left(t \text{ is as extreme or more extreme than } t_{\text{observed}} \;\middle|\; H_0 \text{ true}\right) \\
&= P\left(|t| \geq |t_{\text{observed}}| \;\middle|\; H_0 \text{ true}\right) \quad \leftarrow \text{for a two-sided } t\text{-test}
\end{aligned}
$$



From the p-value to the results of a hypothesis test

We ask whether there is any contradiction between H_0 and the observed data

- The p-value is the probability under the null hypothesis of obtaining a result as extreme or more extreme than the observed result
- A small p-value implies evidence against the null hypothesis
- A large p-value implies no evidence against the null hypothesis

No

If the p-value is large does this imply that the null hypothesis is true?

What does the p-value say about the probability that the null hypothesis is true? Try using Bayes' rule to figure this out.

How small is small?

One approach:

- Set a significance level, α, before conducting the test
- A popular choice is $\alpha = 0.05$
- If the *p*-value is below α, you reject the null hypothesis (and accept H_1)
- An advantage of this approach is that it gets you to think about the problem and the data carefully before data are collected. What α would you really like?

However:

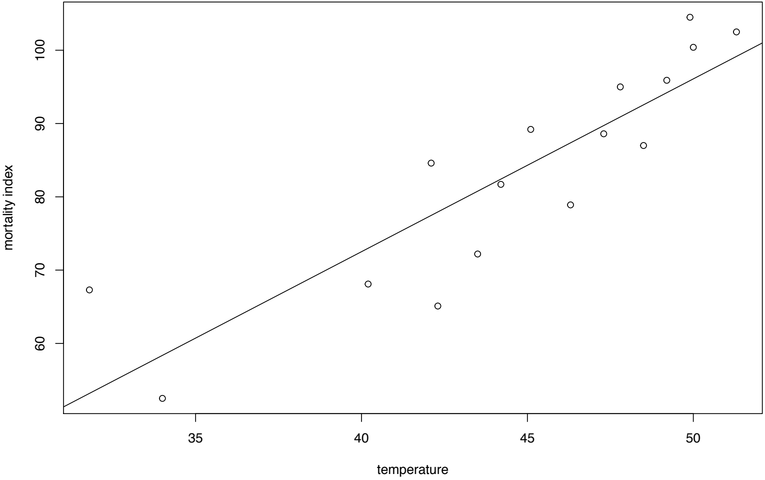
- This approach can be considered wasteful, since *p*-values of 0.04 and 10^{-4} yield the same result
- Ronald Fisher tended to report the *p*-value and let it speak for itself

R combines the best of both worlds, as we'll see

Procedure for a t test

1. Assume the null hypothesis, H_0 and its distribution
2. Calculate your T statistic given H_0
3. Was your observed result plausible? Yes/no: accept H_0/H_1

Returning to the temperature/mortality dataset



R has already calculated our *p*-value

http://blog.yhat.com/posts/r-lm-summary.html

```
summary(myFit)
```

```
##
## Call:
## lm(formula = M ~ T)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12.8358  -5.6319   0.4904   4.3981  14.1200
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -21.7947    15.6719  -1.391    0.186
## T             2.3577     0.3489   6.758  9.2e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

want to see residual normally distributed, close to 0

very significant

Our p-value affects our interpretation

Interpreting b_0 or b_1 when their p-value is low:

- What does the slope mean? For each unit increase in X, Y can be expected to increase by $b_1 X$
- What does the intercept mean? The b_0 has meaning when you are studying very small values of X. It tells you what Y might be when X is around 0

Interpreting b_0 or b_1 when their p-value is high:

- We can say very little in such cases

Extra information: the two-sample t-test

Suppose that there is a clinical trial, in which subjects are randomized to treatments A or B with equal probability. Let μ_A be the mean response in the group receiving drug A and μ_B be the mean response in the group receiving drug B. The null hypothesis is that there is no difference between A and B; the alternative claims there is a clinically meaningful difference between them.

$$H_0 : \mu_A = \mu_B \text{ versus } H_1 : \mu_A \neq \mu_B$$

We want to know if the standard treatment is better than the experimental treatment, or vice versa

The two-sample t-test

Let's assume the patient data are independent random samples from a normal distribution with means μ_A and μ_B but the same variance.

Let's use $\bar{y}_A - \bar{y}_B$ as our test statistic. The distribution is

$$\bar{y}_A - \bar{y}_B \sim \mathcal{N}\left(\mu_A - \mu_B, \sigma^2(1/n_A + 1/n_B)\right).$$

So,

$$\frac{(\bar{y}_A - \bar{y}_b) - \delta_\mu}{\sigma\sqrt{1/n_A + 1/n_B}} \sim \mathcal{N}(0,1)$$

and we can set δ_μ to zero and continue as per slides 28–30.

Today's class

- The Confidence Interval in Linear Regression
- Hypothesis testing on β_0 and β_1
- **Regression Analysis of Variance**
- Reference: Simon Sheather §§2.2 – 2.5

Regression Analysis of Variance

How well does the regression line summarize the data?

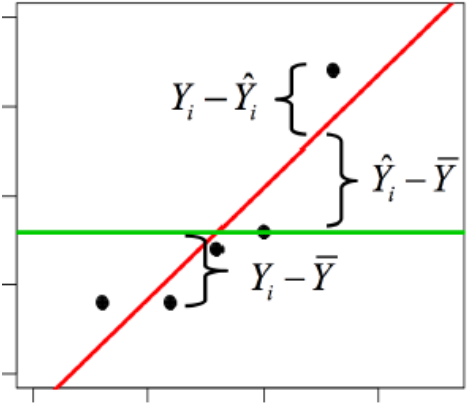
Decomposition of sums of squares:

$$\begin{aligned} y_i &= \hat{y}_i + \hat{e}_i \\ &= b_0 + b_1 x_i + \hat{e}_i \\ &= \bar{y} - b_1\bar{x} + b_1 x_i + \hat{e}_i \\ y_i - \bar{y} &= b_1(x_i - \bar{x}) + \hat{e}_i \end{aligned}$$

Squaring both sides, and summing, leads to:

$$\underbrace{\sum_{i=1}^{n}(y_i - \bar{y})^2}_{\text{SST}} = \underbrace{\sum_{i=1}^{n} b_1^2 (x_i - \bar{x})^2}_{\text{SSReg}} + \underbrace{\sum_{i=1}^{n} \hat{e}_i^2}_{\text{RSS}}$$

The building blocks of ANOVA



Analysis of variance

a.k.a. ANOVA or "Decomposition of SS", where SS = sum of squares

$$\underbrace{\sum_{i=1}^{n}(y_i - \bar{y})^2}_{\text{SST}} = \underbrace{\sum_{i=1}^{n} b_1^2(x_i - \bar{x})^2}_{\text{SSReg}} + \underbrace{\sum_{i=1}^{n} \hat{e}_i^2}_{\text{RSS}}$$

SST ("Total SS"):

- Also known as *Corrected SS*
- This is by comparison with the "uncorrected SS", which is just $\sum_{i=1}^{n} y_i^2$

SSReg ("Model SS" or Regression SS):

- It is the amount of variation in y's explained by the regression line

RSS ("Residual sum of squares", or Error sum of squares):

- The method of least squares minimized this

Exercise

Show that

$$b_1^2 \sum_{i=1}^{n} (x_i - \bar{x})^2 = \sum (\hat{y}_i - \bar{y})^2$$

The ANOVA Table

We usually summarize these quantities as:

Source	SS	d.f.	MS = SS/df
Regression line	$b_1^2 S_{xx} = \sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2$	1	$b_1^2 S_{xx}$
Error	$\sum_{i=1}^{n} \hat{e}_i^2$	$n-2$	S^2
Total	$\sum_{i=1}^{n} (y_i - \bar{y})^2$	$n-1$	–

Coefficient of Determination

R^2 prone to outliers

$$R^2 = \frac{\text{SSReg}}{\text{SST}} = 1 - \frac{\text{RSS}}{\text{SST}}, \quad 0 \leq R^2 \leq 1$$

R^2 gives the percent of variation in y's that is explained by the regression line

In the Montreal Protocol dataset, we have $R^2 \approx \frac{203119}{203993} \approx 99.6\%$

R^2 is useful, but:

- No absolute rules about how big it should be
- Not resistant to outliers (we'll see this next week)
- Not meaningful for models with no intercept
- We can get a very high R^2 by overfitting (complicated model, may fit well for data you have but won't work well on other data)

mean squares are estimators of sum of squares
taking expected value of MSE/MSReg -> what they try to estimate

Mean square of regression = MSReg = SSReg / 1 $= b_1^2 \sum_{i=1}^{n}(x_i - \bar{x})^2$

Think of MSReg as an estimator, $\hat{\beta}_1^2 \sum_{i=1}^{n}(x_i - \bar{x})^2$

$$\mathbb{E}(\text{MSReg}) = \sigma^2 + \beta_1^2 S_{xx}$$

MSE "Mean Square Error" = RSS/$(n-2)$ $= \sum_{i=1}^{n} \hat{e}_i^2/(n-2)$

$$\mathbb{E}(\text{MSE}) = \sigma^2$$

Reminder of distribution theory

If $U \sim \chi^2(\nu_1)$ and $V \sim \chi^2(\nu_2)$, and U and V are independent, then

$$\frac{U/\nu_1}{V/\nu_2} \sim \ ?$$

F_{v_1, v_2}

ANOVA - *F* statistic

- This idea, due to Ronald Fisher, is about comparing variations
- Fisher introduced the method in his 1925 book "Statistical Methods for Research Workers"
- This statistical procedure enables us to answer several questions at once
- Before, the prevailing method was to test one thing at a time
- In the 1925 book, he included one *F* table for various numerator and denominator degrees of freedom
  - The table gave the critical values for only the 5% points
  - As use of the method spread, so did the use of the 5% level (Stephen Stigler, *Fisher and the 5% level*, 2008)

A new hypothesis test

If $\beta_1 = 0$, $\mathbb{E}(\text{MSReg}) = \mathbb{E}(\text{MSE})$.

Moreover, if $\beta_1 = 0$, then $\frac{\text{MSReg}}{\sigma^2} \sim \chi^2(1)$ and $\frac{\text{MSE}(n-2)}{\sigma^2} \sim \chi^2(n-2)$

Therefore, if $\beta_1 = 0$,

$$\frac{\frac{\text{MSReg}}{\sigma^2}/1}{\frac{\text{MSE}(n-2)}{\sigma^2}/(n-2)} \sim F_{1,n-2}$$

This opens up another test of $H_0 : \beta_1 = 0$ vs $H_1 : \beta_1 \neq 0$.

distribution under null

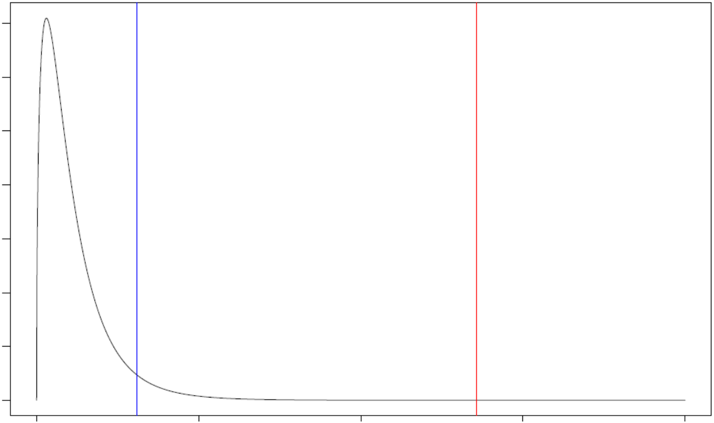
test for if there is a linear relation between X and Y

What is the test statistic?

We can use as our test statistic $F_{\text{obs}} = \frac{\text{MSReg}}{\text{MSE}}$:

- Under H_0, this is an observation from an F distribution with 1 and $n-2$ degrees of freedom
- $\beta_1 \neq 0$ gives larger values of F_{obs}, so deviations from $\beta_1 = 0$ are in the right tail of the F distribution
- On the Montreal Protocol data, we get a high F_{obs}, leading to again get $p < 0.001$. This is strong evidence that β_1 isn't 0.

Example



F versus t

In general, the square of a r.v. with a t_m distribution results in a r.v. with an $F_{1,m}$ distribution.

This approach is more useful in multiple linear regression (more than one predictor), which we'll do after the midterm.

For now, an exercise for you: Show, in general, that $t^2_{\text{obs}} = F_{\text{obs}}$

Of course, equivalent under null only, i.e. beta_1 = 0

Next steps

- Solutions to HW #1 to be posted very soon – last chance to try them without peaking!
- Next TA office hours: tomorrow morning

Exercises:

- Try today's plotting exercise, and the proofs
- Try the seven questions at the back of Chapter 2 in Simon Sheather's textbook
- Use R where it would make things easier

Appendix

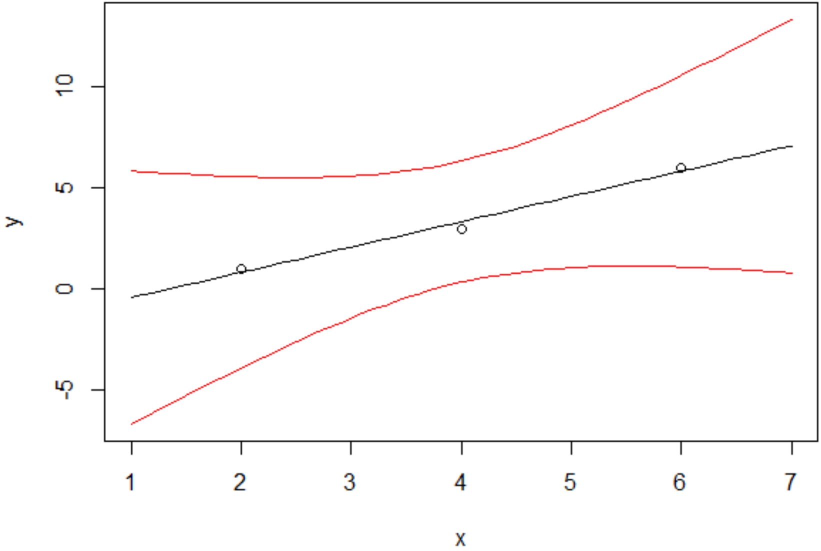
Code for new exercise on slide 15

```
x<-c(2,4,6);  y<-c(1,3,6);  n <- length(x)
mx <- mean(x); my <- mean(y)
Sxx <- sum((x-mx)^2); Sxy <- sum((x-mx)*(y-my))
b1 <- Sxy/Sxx; b0 <- mean(y) - b1*mean(x)
yhat <- b0 + b1*x
RSS <- sum((y-yhat)^2)
S <- sqrt(RSS/(n-2))

xstar <- seq(min(x)-1,max(x)+1,.1) # Points at which to interpolate
ystarMean <- b0+b1*xstar # Interpolations

a <- qt(.975,n-2)*S*sqrt(1/n+(xstar-mx)^2/Sxx) # See slide 14
ystarLow <- ystarMean-a; ystarHigh <- ystarMean+a # Slide 14
plot(x,y,xlim=c(min(xstar),max(xstar)),
     ylim=c(min(ystarLow),max(ystarHigh)))
lines(xstar,ystarMean,type="l",col="black")
lines(xstar,ystarLow,type="l",col="red")
lines(xstar,ystarHigh,type="l",col="red")
```

Output for new exercise on slide 15



Are the regression coefficients different from zero?

```
seB0 <- S*sqrt(1/n+mx^2/Sxx) # standard error; slide 18
seB1 <- S/sqrt(Sxx) # slide 18

t0 <- b0/seB0 # the test statistic for the intercept
t1 <- b1/seB1 # and for the slope
pval0 <- 2*pt(-abs(t0),n-2) # pvalue for the intercept
pval1 <- 2*pt(-abs(t1),n-2) # and the slope

print(c(b0,b1,pval0,pval1))
myFit <- lm(y~x) # Compare calculations to R's own
summary(myFit)
```

manual calculation

Im doing the same thing

Are the regression coefficients different from zero?

Dont think so

```
## [1] -1.6666667  1.2500000  0.2279347  0.0731864


##
## Call:
## lm(formula = y ~ x)
##
## Residuals:
##       1       2       3
##  0.1667 -0.3333  0.1667
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -1.6667     0.6236  -2.673   0.2279
## x             1.2500     0.1443   8.660   0.0732 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4082 on 1 degrees of freedom
## Multiple R-squared:  0.9868, Adjusted R-squared:  0.9737
## F-statistic:    75 on 1 and 1 DF,  p-value: 0.07319
```

equivalent test

What are the confidence intervals for β_0 and β_1?

now look at confidence interval

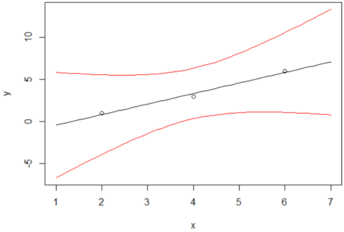
```
d0 <- qt(.975,n-2)*seB0 # See slide 19
d1 <- qt(.975,n-2)*seB1
b0Low <- b0-d0; b0High <- b0+d0 # Slide 19
b1Low <- b1-d1; b1High <- b1+d1
print(round(c(b0Low,b0,b0High,b1Low,b1,b1High),2))
```

```
## [1] -9.59 -1.67  6.26 -0.58  1.25  3.08
```

encapsulate 0, so cant reject null -> significant

Prediction Intervals

The straight line we have plotted is our best estimate of the population regression line, $\mathbb{E}(Y|X=x^*)$ for various x^*. The pointwise confidence intervals (red lines) reflect our uncertainty in this population regression line.



What if we were predicting a new data point at $x^* = 7$ — what would our best estimate of that new point's ordinate be?

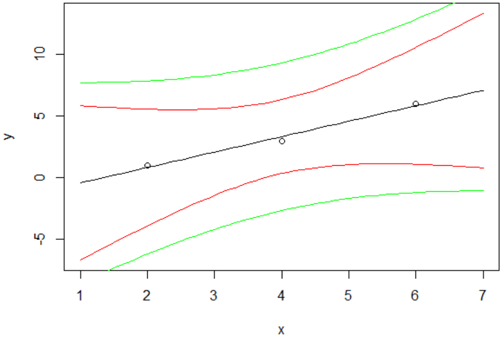
Clearly we'd pick a point on the black line. What about the plus-minus? It isn't the red lines, but instead something called a **prediction interval**.

Prediction Intervals

A prediction interval reflects that when a new data point is generated according to our model, there is a model error term, e_i, deflecting it from the population regression line. Recall:

$$Y_i = \beta_0 + \beta_1 x_i + e_i$$

While a *parameter* has a confidence interval, a *random variable* has a prediction interval. (Here, the r.v. is Y^*.)



Deriving the prediction interval

The error in our prediction is

$$
\begin{aligned}
Y^* - \hat{y}^* &= \beta_0 + \beta_1 x^* + e^* - \hat{y}^* \\
&= \mathbb{E}(Y|X = x^*) - \hat{y}^* + e^*
\end{aligned}
$$

It's straightforward to show that its expectation is zero. The variance is:

$$
\begin{aligned}
\mathrm{var}(Y^* - \hat{y}^*) &= \mathrm{var}(Y|X = x^*) + \mathrm{var}(\hat{y}|X = x^*) - 2\mathrm{cov}(Y, \hat{y}|X = x^*) \\
&= \sigma^2 + \sigma^2 \left[\frac{1}{n} + \frac{(x^* - \bar{x})^2}{S_{xx}}\right] - 0 \\
&= \sigma^2 \left[1 + \frac{1}{n} + \frac{(x^* - \bar{x})^2}{S_{xx}}\right]
\end{aligned}
$$

Derivation continued

Since both $\hat{y}$ and Y^* are normally distributed,

$$Y^* - \hat{y}^* \sim \mathcal{N}\left(0,\, \sigma^2\left[1 + \frac{1}{n} + \frac{(x^* - \bar{x})^2}{S_{xx}}\right]\right)$$

Standardizing and replacing σ by S, as we did on slides 9–10, gives

$$T \;=\; \frac{Y^* - \hat{y}^*}{S\sqrt{1 + \frac{1}{n} + \frac{(x^* - \bar{x})^2}{S_{xx}}}} \;\sim\; t_{n-2}$$

Derivation continued

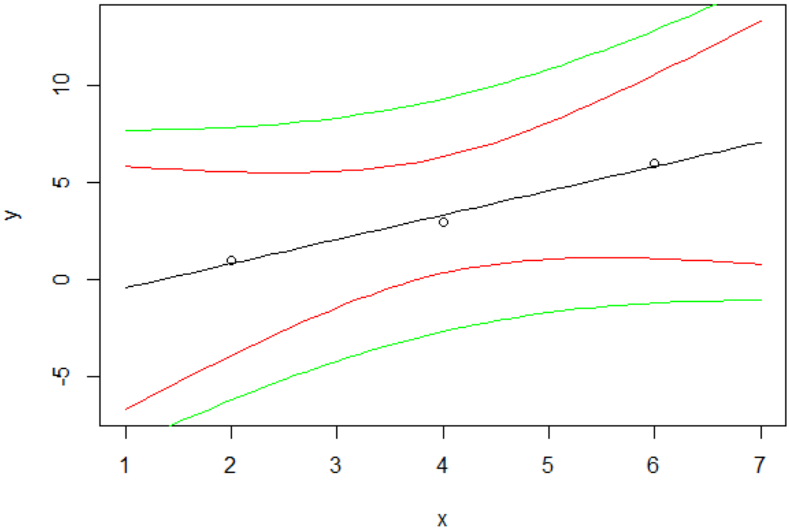
And therefore the $100(1-\alpha)\%$ prediction interval for Y^* is:

$$\hat{y}^* \;\pm\; t(\alpha/2, n-2)\; S\sqrt{1+\frac{1}{n}+\frac{(x^*-\bar{x})^2}{S_{xx}}}$$
$$=\;\left(\hat{\beta}_0+\hat{\beta}_1 x^*\right)\;\pm\; t(\alpha/2, n-2)\, S\sqrt{1+\frac{1}{n}+\frac{(x^*-\bar{x})^2}{S_{xx}}}$$

Prediction Interval example

```
f <- qt(.975,n-2)*S*sqrt(1+1/n+(xstar-mx)^2/Sxx)
ystarPredLow <- ystarMean-f; ystarPredHigh <- ystarMean+f
plot(x,y,xlim=c(min(xstar),max(xstar)),
     ylim=c(min(ystarPredLow),max(ystarPredHigh)))
lines(xstar,ystarMean,type="l",col="black")
lines(xstar,ystarPredLow,type="l",col="green")
lines(xstar,ystarPredHigh,type="l",col="green")
```

Prediction Interval example



Poll question

For a 95% confidence interval that you've calculated,

- A: 95% of the sample data lie within the interval
- B: It is a definitive range of plausible values for the sample parameter
- C: If the experiment is repeated, there is a 95% probability that the new sample's estimate of the parameter will fall within this interval
- D: There is a 95% probability that the population parameter lies within the interval
- E: None of the above

false, because once experiment done, CI either encompasses or did not encompass the true population parameter

To vote: visit pollev.com/MARKEBDEN209 *or*

- Text MARKEBDEN209 to short code 37607
- Text A, B, C, D, or E

if CI constructed using confidence level,
given infinite number of experiments, proportion of interval
containing true value of parameter will match confidence level

Statistical coverage

When an experiment is repeated many times, **coverage** refers to the proportion of the time that an interval contains the true value of interest.

Setting $\beta_0 = -2$, $\beta_1 = 1$, $\sigma = 1$, $\mathbf{x} = [2, 4, 6]$, and $X^* \sim \text{Unif}(0, 8)$, we can "play God" and create 10,000 datasets.

The confidence intervals and prediction intervals ought to encapsulate the truth about 95% of the time.

Indeed they do. The following data are the statistical coverage for the CI for $\mathbb{E}(Y|X = x^*)$, PI for y^*, CI for β_0, and CI for β_1. The code was run three times.

94.79	95.12	94.61	94.66
95.01	95.11	95.09	95.04
95.15	95.23	94.87	94.92

R code to analyse coverage

```r
N <- 10000
beta0 <- -2; beta1 <- 1; sigma <- 1
x<-c(2,4,6); n <- length(x)
mx <- mean(x); Sxx <- sum((x-mx)^2);
ciY <- matrix(0,nrow=N,ncol=2)
piY <- matrix(0,nrow=N,ncol=2) # prediction intervals on Ystar
ciB <- matrix(0,nrow=N,ncol=6) # confidence intervals on B0 and B1
Ys <- rep(0,N) # Actual y_star
ystar <- rep(0,N) # true population line at xstar

for (i in 1:N) {
  y <- beta0 + beta1*x + rnorm(3,0,sigma)
  my <- mean(y)
  Sxy <- sum((x-mx)*(y-my))
  b1 <- Sxy/Sxx; b0 <- mean(y) - b1*mean(x)
  yhat <- b0 + b1*x
  RSS <- sum((y-yhat)^2); S <- sqrt(RSS/(n-2))

  # New point
  xstar <- runif(1,0,8) # Point at which to interpolate
  ystarMean <- b0+b1*xstar # Interpolation
  ystar[i] <- beta0+beta1*xstar # population line at xstar
  Ys[i] <- ystar[i] + rnorm(1,0,sigma) # Actual sampled point at xstar

  # Confidence interval on Y*
  a <- qt(.975,n-2)*S*sqrt(1/n+(xstar-mx)^2/Sxx) # See slide 14
  ystarLow <- ystarMean-a; ystarHigh <- ystarMean+a # Slide 14
  ciY[i,] <- c(ystarLow,ystarHigh)

  # Prediction interval
  f <- qt(.975,n-2)*S*sqrt(1+1/n+(xstar-mx)^2/Sxx) # See appendix of Week 3
  YstarPredLow <- ystarMean-f; YstarPredHigh <- ystarMean+f
  piY[i,] <- c(YstarPredLow, YstarPredHigh)

  # Confidence intervals on parameters:
  seB0 <- S*sqrt(1/n+mx^2/Sxx) # standard error; slide 18
  seB1 <- S/sqrt(Sxx) # slide 18
  d0 <- qt(.975,n-2)*seB0 # See Week 3 slide 19
  d1 <- qt(.975,n-2)*seB1
  b0Low <- b0-d0; b0High <- b0+d0 # Week 3, Slide 19
  b1Low <- b1-d1; b1High <- b1+d1
  ciB[i,]<-c(b0Low,b0,b0High,b1Low,b1,b1High)
}

coverageCIY <- sum(ystar > ciY[,1] & ystar < ciY[,2])/N*100
coveragePIY <- sum(Ys > piY[,1] & Ys < piY[,2])/N*100
coverageCIB0 <- sum(beta0 > ciB[,1] & beta0 < ciB[,3])/N*100
coverageCIB1 <- sum(beta1 > ciB[,4] & beta1 < ciB[,6])/N*100
print(c(coverageCIY,coveragePIY,coverageCIB0,coverageCIB1))
```

Statistical coverage for estimating the mean of a uniform distribution

Consider a r.v. $X \sim \text{Unif}(\theta - 1, \theta + 1)$. Suppose we wish to estimate the mean, θ, by drawing two observations x_1 and x_2.

The ordered pair of observations is a 50% confidence interval for θ, because:

- $P(X_1 < \theta) = 0.5$
- $P(X_2 < \theta) = 0.5$
- Therefore, $P(X_1 < \theta \ \cap \ X_2 < \theta) = 0.25$
- Similarly, $P(X_1 > \theta \ \cap \ X_2 > \theta) = 0.25$
- Therefore, $P(X_1 < \theta < X_2 \ \cup \ X_2 < \theta < X_1) = 0.5$
- Thus, X_1 and X_2 will form* a 50% confidence interval

If you draw a pair of observations and check whether θ is in between, about half of the time the answer should be yes.

* Note that r.v.'s X_1 and X_2 will be sampled as (observed) x_1 and x_2.

Statistical coverage for the mean of a uniform distribution

```r
N <- 10000 # number of times to draw a pair of observations
theta <- 4 # true mean of uniform distribution
x1 <- runif(N,theta-1,theta+1)
x2 <- runif(N,theta-1,theta+1)
xObs <- data.frame(x1,x2) # arrange the observations
xObs <- t(apply(xObs, 1, sort)) # sort per pair of observations

# Count how many times the CI contains theta:
coverageCI <- sum(xObs[,1]<theta & theta<xObs[,2])
print(coverageCI/N*100) # should be about 50%
```

The results of three runs were indeed all around 50%:

```
50.33
50.62
49.71
```

An interesting perspective provided by this experiment

You've probably noticed that x_1 and x_2 can be anywhere from 0 to 2 apart.

If the two observations are more than 1 unit apart (which should happen about $1/4$ of the time), they must contain θ. Therefore, $P(\theta \text{ is encapsulated} \mid \text{CI} > 1) = 1 \neq 0.5$.

```
> xobs[1:10,]
          [,1]     [,2]
 [1,] 4.523547 4.774419
 [2,] 3.017677 4.630479   *
 [3,] 4.224326 4.502110
 [4,] 4.857525 4.906798
 [5,] 3.077431 4.647262   *
 [6,] 3.912724 4.520368
 [7,] 3.208084 4.258985   *
 [8,] 4.307776 4.788264
 [9,] 3.406603 4.750983   *
[10,] 3.657361 4.493136
```

An interesting perspective provided by this experiment

This experiment underlines the fact that a calculated 95% CI should *not* be interpreted as "With 95% probability, the true parameter is in this range". Instead, that CI is a realization of a process that covers the true parameter 95% of the time.

Slides 38–50