

***This is not an exhaustive list of things to know for midterm 2!*** It's a collection of stuff I found in previous midterms that caught my eye for one reason or another. Maybe I found it difficult compared to the rest, maybe I found it to be a relatively obscure piece of information, or maybe I'm just weird. So caveat emptor.

## Midterm 2, 2014

**MT2 2014 - Problem 2e.** We regress mean charge on mean cost – we want to try to use mean cost to explain mean charge, so

$$\text{meancharge}_i = \beta_1 + \beta_2 \text{meancost}_i + u_i.$$

“The claim is made that the mean charge increases with the mean cost.” In other words, we want to estimate  $\beta_2$  and see whether it's positive or negative. If it's positive, then mean change is increasing in mean cost. *The alternative hypothesis is our claim*, which might feel a bit counterintuitive at first. Which is to say, our test is

$$H_0 : \beta_2 \leq 0,$$

$$H_A : \beta_2 > 0.$$

This goes back to the fact that we either reject or do not reject the null, but we never *accept* the null. So our way of being comfortable saying that  $\beta_2 > 0$  is by (potentially) rejecting the opposite of our claim, i.e.  $\beta_2 \leq 0$ .

This is also why the  $p$ -values shown after running a regression are based on a null hypotheses of  $H_0 : b_i = 0$ .

**MT2 2014 - Problem 3b.** The regression output of  $\text{meancharge}_i = \beta_1 + \beta_2 \text{meancost}_i + u_i$  gives  $b_2 = 1.314908$ . The interpretation is: a \$1 increase in mean cost is associated with a \$1.314908 increase in mean charge. **It is tempting but incorrect** to divide both sides by 1.314908 and say that a \$1 increase in mean charge is associated with a \$1/1.314908 increase in mean cost. The correct answer is that there is not enough information know.

**MT2 2014 - Problem 4.** The term “regression sum of squares” is the same as “explained sum of squares.” It's selling us the total squared variation of  $y_i$  around  $\bar{y}$  explained by the regressor  $x$ . Don't get tricked into thinking “regression sum of squares” is RSS – that would be “residual sum of squares” instead.

**MT2 2014 - Multiple Choice 2.** This is an ugly one and I can't really comment on how likely something like this is to appear on our midterm. Anyway, we can automatically cross

off options (a) and (b) and thus (d) just by noting that

$$r_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \times \sum_{i=1}^n (y_i - \bar{y})^2}} = \frac{s_{xy}}{\sqrt{s_x^2 \times s_y^2}},$$

$$b_2 = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2},$$

aren't going to give the same result in general because the denominators are different. So the question is whether (c) is valid or not.

The brute-force way to solve this is to take the equation for  $b_2$  and plug the  $z$ -score  $(x - \bar{x})/s_x$  into the regressor place, and the other  $z$ -score  $(y - \bar{y})/s_y$  where the dependent variable goes. For this to work, though, we need to know what the means are. Easier than it might seem – these terms are standardizations, so they have mean zero. Thus we can go

$$\begin{aligned} b_2^z &= \frac{\sum_{i=1}^n \left( \frac{x_i - \bar{x}}{s_x} - 0 \right) \left( \frac{y_i - \bar{y}}{s_y} - 0 \right)}{\sum_{i=1}^n \left( \frac{x_i - \bar{x}}{s_x} - 0 \right)^2} \\ &= \frac{\sum_{i=1}^n \left( \frac{x_i - \bar{x}}{s_x} \right) \left( \frac{y_i - \bar{y}}{s_y} \right)}{\sum_{i=1}^n \left( \frac{x_i - \bar{x}}{s_x} \right)^2} \\ &= \frac{\frac{1}{s_x s_y} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\frac{1}{s_x s_x} \sum_{i=1}^n (x_i - \bar{x})^2} \\ &= \frac{s_x \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{s_y \sum_{i=1}^n (x_i - \bar{x})^2}. \end{aligned}$$

If we multiply numerator and denominator both by  $1/(n-1)$ , we get covariance  $s_{xy}$  and variance  $s_x^2$ , respectively. So uh, do that.

$$\begin{aligned} b_2^z &= \frac{s_x \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{s_y \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2} \\ &= \frac{s_x s_{xy}}{s_y s_x^2} \\ &= \frac{s_{xy}}{\sqrt{s_x^2 \times s_y^2}} \\ &= r_{xy}. \end{aligned}$$

**MT2 2014 - Multiple Choice 5.** The intuition for choice (a) is that we can be more confident about hitting a larger target. Think of the confidence interval of being that target. Thus, higher confidence is wider confidence interval. If we go from, say, 95% confidence to 90% confidence, then our confidence interval becomes smaller – we’re less confident about hitting a smaller target.

For choice (b), think back to confidence intervals from midterm 1,

$$\bar{x} \pm t \times \frac{s_x}{\sqrt{n}}.$$

As  $n$  gets bigger, the term we’re subtracting/adding from  $\bar{x}$  gets smaller and smaller, and thus the confidence interval gets closer and closer to  $\bar{x}$ . This isn’t exactly true in the regression case, but it is analogous – standard errors are decreasing in  $n$ .

## Midterm 2, 2015

**MT2 2015 - Problem 1a.** If you’re dealing with confidence intervals and you aren’t given  $t$ -values, then you have to use a rough guess. Commonly used rules-of-thumb are

$$95\% \implies 1.96, \quad (\text{or even just } 2)$$

$$90\% \implies 1.64,$$

$$99\% \implies 2.57.$$

**MT2 2015 - Multiple Choice 1.** When doing hypothesis testing, we first choose size – this is the, say, 0.05 significance level at which we test. Then, after having chosen our size, we want to choose the test that maximizes the power of that test. For our purposes, this is whether or not we decide to do a one- or two-sided test.

**MT2 2015 - Multiple Choice 2.** Under assumptions 1-2,

$$\begin{aligned} E[y|x = x^*] &= E[b_1 | x = x^*] + E[b_2x | x = x^*] + E[u | x = x^*] \\ &= \beta_1 + \beta_2x^* + 0. \end{aligned}$$

Assumptions 1-2 imply unbiased estimators, so we know the expectations of the estimated coefficients  $b_i$  will be the population parameters  $\beta_i$ . Assumption 2 is that  $E[u | x] = 0$ .

## Midterm 2, 2016

**MT2 2016 - Problem 1d.** See my really long answer in MT2 2014. Short answer is, if you regress  $(y - \bar{y})/s_y$  on  $(x - \bar{x})/s_x$ , you get the the correlation coefficient  $r_{xy} = 0.6$ .

Square that and you have  $R^2 = 0.36$ , which tells you the (squared and summed) proportion of variation of  $y$  around its mean that can be explained by  $x$ .

**MT2 2016 - Problem 1e.**

- Type I error: rejecting  $H_0$  when  $H_0$  is true.
- Type II error: not rejecting  $H_0$  when  $H_0$  is false.
- Size:  $Pr(\text{Type I error})$
- Power:  $1 - Pr(\text{Type II error})$

**MT2 2016 - Multiple Choice 1.** To find correlation, we divide the covariance by  $s_x s_y$ , both of which are always positive. Hence the sign does not change.

**MT2 2016 - Multiple Choice 5.** See MT2 2015 multiple choice number 2. The idea is that the zero conditional mean assumption (the second assumption) makes the residuals – the prediction “mistakes” our model makes – disappear when we consider the conditional expectations. In other words, the residuals become irrelevant in conditional expectation. This allows us to “shrink the target” while remaining 95% confident.