# STA302/STA1001, Weeks 8-9

Mark Ebden, 31 October & 2 November 2017

With grateful acknowledgment to Alison Gibbs

## Plan for Tuesday 31 October

- Section 1 can pick up midterms and digest them for a few minutes
- ▶ Midterm discussion
- ► Chapter 5
- ▶ One-to-one discussion about any midterm issues



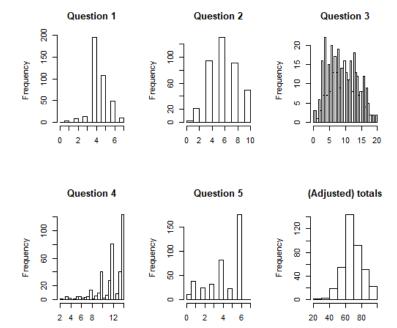
#### Midterms: Section 1



The number of test takers was 406 in Section 1: STA302/1001 LEC0101 & LEC2001.

Marking has been completed for Section 1 only.

# Midterm marks: Based on 96% of test papers in Section 1



#### Midterm marks: Section 1

#### Raw scores:

- ▶ Top students got 55/57
- ► Average of 64%

#### Adjusted scores:

- ► Two marks of 100%
- ► Average of 68.3%

#### Questions:

- ▶ Questions 1, 2, and 5 had averages of 62 to 64%
- ► Hardest question was #3: average was 47%
- ► Easiest question was #4: average was 84%
- ▶ We'll review some of these in a moment

### To request a re-grade: Section 1

By 9 November, please email sta302sec1@gmail.com with a description of the problem, including whether or not you spoke with me during class on 31 October.

You should receive a reply within a week of sending your request, and your mark may go up or down.



For efficiency, you may wish to include a picture of the problem. This is encouraged but optional. If the picture you take isn't found to match what we have on record, when verified at a later date, then you may be subject to an academic offence and any previous mark adjustment would be moot.

#### Post-midterm work so far

- ▶ §3.3 (Transformations) except for Box-Cox transformations and inverse-response plots
- §5.2 (Estimation and Inference in MLR) is what we've been heading towards, via the RMA



# A closer look at $\mathbf{X}'\mathbf{X}$ and $(\mathbf{X}'\mathbf{X})^{-1}$

Previously we simplified 
$$\mathbf{X}'\mathbf{X}$$
, for  $\mathbf{X} = \begin{pmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_n \end{pmatrix}$ 

We began to consider  $(\mathbf{X}'\mathbf{X})^{-1}$  (Week 8, slide 12), because of its appearance in  $\hat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}$ .

This  $\hat{\beta}$  expression is a concise way to write the estimators for linear regression, compared to  $\hat{\beta}_1 = \frac{S_{xy}}{S_{xx}} = \frac{\sum_{i=1}^n x_i y_i - n \bar{x} \bar{y}}{\sum_{i=1}^n x_i^2 - n \bar{x}^2}$  and  $\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$ .

## Properties of least squares estimates

Recall that  $E(\hat{\beta}_0) = \beta_0$  and  $E(\hat{\beta}_1) = \beta_1$ , and that

$$\mathsf{var}\left(\hat{\beta}_1\right) = \frac{\sigma^2}{\mathsf{S}_\mathsf{xx}}, \qquad \mathsf{var}(\hat{\beta}_0) = \sigma^2 \left[\frac{1}{\mathsf{n}} + \frac{\bar{\mathsf{x}}^2}{\mathsf{S}_\mathsf{xx}}\right] \quad \mathsf{and} \quad \mathsf{cov}(\hat{\beta}_0, \hat{\beta}_1) = -\frac{\sigma^2 \bar{\mathsf{x}}}{\mathsf{S}_\mathsf{xx}}$$

Let's now confirm that our new equations give this as well.



### Next steps

- ▶ HW2 (not for credit) is on Portal
- ▶ We'll continue in Chapter 5
  - ▶ More parallels between the old- and new expressions
  - ► MLR (multiple linear regression)



# Appendix: Content for 2 November



#### Missed lectures this week?

You can still pick up your test before the break. Come to SS 6027 CLTA on Friday 3 November from 10-11 am. If you're unable to attend that time as well, you can email me and send a friend/classmate on your behalf.

This is your last opportunity prior to the deadline for regrading requests (9 November for Section 1).



### Recall our R code for $\beta_0$ and $\beta_1$

e.g. from Weeks 5-6, slide 3, handling question 1 of Chapter 2:

```
X <- read.csv("playbill.csv")
y <- X$CurrentWeek; x <- X$LastWeek
my <- mean(y); mx <- mean(x); n <- length(x)
Sxy <- sum((x-mx)*(y-my)); Sxx <- sum((x-mx)^2)
b1 <- Sxy/Sxx # (2.4), beta-hat-1
b0 <- my - b1*mx # (2.3), beta-hat-0
yHat <- b1*x + b0 # (2.1)</pre>
```

## Application of the matrix approach to a small but real dataset

```
Q <- read.csv("playbill.csv")
Y <- Q$CurrentWeek; n <- length(Y)
X <- matrix(c(rep(1,n),Q$LastWeek),ncol=2,byrow=FALSE)
BetaHat <- solve(t(X)%*%X)%*%t(X)%*%Y
Yhat <- X%*%BetaHat
print(BetaHat)</pre>
```

```
## [,1]
## [1,] 6804.8860355
## [2,] 0.9820815
```

%\*% matrix multiplication solve() find inverse

Optional material: In "Octave", BetaHat = inv(X'\*X)\*X'\*Y

# Fitted values $(\hat{\mathbf{Y}})$ in matrix form

Recall from slide 21 in Weeks 6-7 that our model is:

$$Y = X\beta + e$$

Recalling that  $\hat{\beta}$  is unbiased and that  $\mathrm{E}(\mathbf{e})=\mathbf{0}$ , we have  $\widehat{\mathbf{Y}}=\mathbf{X}\hat{\beta}$ . So:

$$\widehat{\mathbf{Y}} = \mathbf{X} \hat{\boldsymbol{eta}} = \mathbf{X} (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\mathbf{Y} = \mathbf{H}\mathbf{Y}$$

where  $\mathbf{H} = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$  is the **hat matrix**, comprised of the  $h_{ij}$  values.

#### Re-"cap"

Recall from weeks 4-5 that h in  $h_{ij}=\frac{1}{n}+\frac{(x_i-\bar{x})(x_j-\bar{x})}{S_{xx}}$  stands for "hat". This is because, considering  $\hat{y}_i=\sum_{j=1}^n h_{ij}\,y_j$ , the h values show how to get from  $y_i$ 's to  $\hat{y}_i$ 's.

This is even more apparent in the matrix notation.



### Properties of **H**

 $\mathbf{H} = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$  is an example of an *idempotent* matrix. Exercise: Show this.

H is symmetric. Exercise: Show this Prove  $H^2 = H$ 

## Five facts about idempotent matrices

- 1. A square matrix **A** is idempotent iff  $\mathbf{A}^2 = \mathbf{A}$
- 2. If **A** is idempotent then  $trace(\mathbf{A}) = rank(\mathbf{A})$
- 3. **A** is idempotent iff rank(**A**) + rank(**I A**) = n where the dimensions of **A** are  $n \times n$  and **I** is the  $n \times n$  identity matrix
- For hat matrix H and matrix of all 1's J, the following matrices are idempotent:

H I-H 
$$\frac{1}{n}$$
J H- $\frac{1}{n}$ J

5. If A, B, and C are idempotent and A = B + C, then rank(A) = rank(B) + rank(C)

iff = "if and only if"

## Residuals $(\widehat{\mathbf{e}})$ in matrix form

The residuals are given by

$$\widehat{\mathbf{e}} = \begin{pmatrix} \widehat{\mathbf{e}}_1 \\ \vdots \\ \widehat{\mathbf{e}}_n \end{pmatrix} = \mathbf{Y} - \widehat{\mathbf{Y}} = \mathbf{Y} - \mathbf{X}\widehat{\boldsymbol{\beta}}$$

Donning our new hat matrix, this can be rewritten as  $\hat{\mathbf{e}} = \mathbf{Y} - \mathbf{H}\mathbf{Y}$  before determining  $\mathrm{E}(\hat{\mathbf{e}})$  and  $\mathrm{var}(\hat{\mathbf{e}})$ .

To begin, how could we factorize  $\hat{\mathbf{e}} = \mathbf{Y} - \mathbf{H}\mathbf{Y}$ ?

# Properties of I - H

Is I - H idempotent?

Is  $\mathbf{I} - \mathbf{H}$  symmetric?

# Continuing:

$$E(\widehat{\mathbf{e}}) =$$

$$\text{var}(\widehat{\mathbf{e}}) =$$

## We hope you have an enjoyable week

- Remember that for the Study Break of 6-10 November, there will be a pause in lectures, TA office hours, and my office hours
- Around the time of the next lecture, there will be a poll on Piazza to ask how *cumulative* you'd like the exam content to be (four options). The final poll results will be discussed with TAs and a nonzero percentage of pre-midterm material will be set

