

Mistake in practice midterm

$$W = \sum_{i=1}^5 (x_i - \bar{x}_i)$$

should be

$$W = \sum_{i=1}^5 (x_i - \bar{x})^2$$

The midterm (of necessity) does NOT cover all the material : insufficient time.

Things that MIGHT be on the real midterm that are NOT on the practice midterm include:

- relationship between M.L.E and the least-squares
- Hill Criteria
- Model Matrix / Design Matrix.

If we write $Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon$

We have a table of data:

Y	1	X_1	X_2
Y_1	1	$X_{1,1}$	$X_{2,1}$
Y_2	1	$X_{1,2}$	$X_{2,2}$
Y_3	1	$X_{1,3}$	$X_{2,3}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$

← This part is the "design matrix".

or

"model matrix"

R command : `model.matrix`.

If our model specified "no intercept" or

$\beta_0 = 0$, `model.matrix` would return

$X_{1,1}$	$X_{2,1}$
$X_{1,2}$	$X_{2,2}$
$X_{1,3}$	$X_{2,3}$
$\vdots$	$\vdots$

instead of the above
(with col of 1s)

Hill Criteria:

One way to get multiple-choices Qs about the Hill Criteria is to ask a LLM.

If you do this: warning: the names of the Hill Criteria in the text are not universal.
e.g. "Coherence" instead of "Plausibility".

The Hill Criteria are NOT an exact science:

the connection may be causal even if some of the Hill Criteria are not satisfied.

It's also possible to have all the criteria satisfied and not have a causal connection.

(maybe you overlooked an important covariate?)

Another idea to prepare for midterm: paste questions from midterm in to LLM and tell it:
give me an analogous question.

No further homework until after midterm 1.

The "Hat Matrix" gets its name because it "puts a hat" on Y .

$$\hat{Y} = H \cancel{X} Y \quad \text{where} \quad H = X(X^T X)^{-1} X^T$$

$\hat{Y}$ is called the "fitted values" vector.

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_i \quad \text{in the 1-variable case.}$$

$\hat{Y}_i$ is the point on the regression line:

it is our "point estimate" of Y given the particular X -value

Things to know about the hat matrix:

it is the projection matrix on the col space of X .

So $H^2 = H$. (This is also directly computable.)

$$\begin{aligned} H^2 &= X(X^T X)^{-1} \underbrace{X^T X (X^T X)^{-1}}_{= I} X^T \\ &= X(X^T X)^{-1} X^T = H. \end{aligned}$$

and H is symmetric $H^T = H$.

Using your linear algebra (304)

$$\begin{aligned} H^T &= \left(X (X^T X)^{-1} X^T \right)^T = (X^T)^T \left((X^T X)^{-1} \right)^T X^T \\ &= X \left((X^T X)^T \right)^{-1} X^T \\ &= X \left(X^T (X^T)^T \right)^{-1} X^T \\ &= H. \end{aligned}$$

Note that the residuals e_i are defined by

$$Y_i = \hat{\beta}_0 + \hat{\beta}_1 X_i + e_i \quad (1\text{-var. case})$$

$$\text{or: } Y_i - \hat{Y}_i = e_i$$

↑
actual value of Y

point on regression
line at same X -val.

So the vector of residuals e is:

$$e = (I - H) Y$$

Connection between $\hat{Y}$ and R^2 (Chap. 2)
(p. 23)

$$R^2 = \text{Cor}(\hat{Y}, Y)^2$$