will be similar,

1) interpret the box,

$\beta_1 \rightarrow$ slope is significant
log odds is increasing over the term

2) Normal distribution $\rightarrow$ recall in logistic regression, we don't independently estimate the mean and variance

- in classic OLS, we could use the t-distribution

3) don't do Cook's and leverage

overpredicting on the left and right and underpredicting in the middle.

4) <u>Indicator var.</u>

$\beta_1 \rightarrow$ not sig.
$\beta_2 \rightarrow$ sig.

Attendance on zoom before sep 10 was significantly lower than afterwards. All other inputs are not sig.

5) likelihood ratio test (chi-sq. dist.) DoF = change in # param. $(\underset{\text{model 2}}{4} - \underset{\text{model 1}}{2} = 2)$
$\hookrightarrow -2\log(LR) \xrightarrow{d} \chi^2(..)$ (Wilks theorem)

6) model 2 better fits the data than model 1.

7)

II

1) $\hat{\beta} = (X^T X)^{-1} X^T Y$

2) Recall Gauss Markov.

$E[\varepsilon_i] = 0$
$Var[\varepsilon_i] = \sigma^2$
$Cov(\varepsilon_i, \varepsilon_j) = 0$

3) $Y - \hat{Y} = Y - X\hat{\beta} = (I - X(X^T X)^{-1} X^T) Y$

$E[r] = E[(I-P)Y] = (I-P) \cdot E[Y]$
$= (I-P) X\beta$

$= X\beta - X\beta = 0$, $PX\beta = X\beta$ from (assignment)

$Var[r] = Var[(I-P)Y] = (I-P) Var Y (I-P)^T$
$= (I-P) \sigma^2 I (I-P)$
$= \sigma^2 . (I-P)^2 = \sigma^2 (I-P)$

4) $Cov(r, \hat{\beta})$ = (use definitions)
$= Cov((I-P)Y, (X^T X)^{-1} X^T Y)$
$= (I-P) \, cov(Y, Y) [(X^T X)^{-1} X^T]^T$
$= (I-P) \sigma^2 I \; X (X^T X^{-1})^{-1}$
$= \sigma^2 [X - X] (X^T X)^{-1} = 0$

5) Note that the 1^{st} col. in X is all 1's and $\sum \hat{e}_i = \underset{\text{vector}}{\mathbb{1}} \cdot e$

$= 1 \cdot [(I - P) Y]$

$= [I - P] \mathbb{1} = 1 - 1 = 0$

$= 0.$

VI HW Qs.

IX Confidence ellipsoid interpretation