# Homework 3

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# 1 Classification

### 7.B.1

a

True: since from the definition of the CDF/PDF relationship:

$$\frac{\partial\Phi(x)}{\partial x}=\phi(x)$$

b

True: again, this is a basic CDF/PDF relationship:

$$\int_{-\infty}^{x} \phi(z)dz = \Phi(x)$$

 $\mathbf{c}$ 

False: this is a basic calculus definition:

$$\int_{x}^{x} \phi(z)dz = 0$$

 $\mathbf{d}$ 

True: From above, and part e:

$$\int_x^x \phi(z)dz + \int_{-\infty}^x \phi(z)dz = 0 + \Phi(x)$$

 $\mathbf{e}$ 

True: Basic CDF/PDF relationship:

$$\int_{-\infty}^{x} \phi(z)dz = \Phi(x)$$

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 $\mathbf{f}$ 

True: Given CDF/PDF relationship:

$$P(x < Z < x + h) = \lim_{x \to h} \int_{x}^{x+h} \phi(z)dz$$
$$= \Phi(x+h) - \Phi(x)$$

And basic calculus:

$$\lim_{x \to h} \frac{\Phi(x+h) - \Phi(x)}{h} = \phi(x)$$

Thus:

$$P(x < Z < x + h) = h\phi(x)$$

#### 7.B.2

a

 $X_i$  is a column vector of 1 (the intercept), the educational level in years of school the individual has attended, the income level of the individual in dollars, and the gender of the individual (1 for male, 0 for female).  $\beta_i$  is a column vector of the weights associated with for the probit model.

b

Random and Latent

 $\mathbf{c}$ 

 $U_i$  is i.i.d. N(0,1), and independent of the prediction variables.

 $\mathbf{d}$ 

The log likihood function is a sum with one term for each subject.

#### 1.1

False.

Difference = 
$$\Phi(X'_{Harry}\beta) - \Phi(X'_{George}\beta)$$
  
=  $\Phi(.29) - \Phi(.19)$   
=  $3.87\%$ 

# 7.B.3

I think I will be using  $x_i$  in the opposite orientation that the authors of the paper do.

### Proof of 5.1

Given  $(X_i'X_i)^{-1} = (X'X - x_ix_i')^{-1}$ , and the Sherman Morrison formula:

$$(X_i'X_i)^{-1} = (X'X)^{-1} + \frac{(X'X)^{-1}x_ix_i'(X'X)^{-1}}{1 - x_i'X^{-1}x_i}$$
$$= (X'X)^{-1} + \frac{(X'X)^{-1}x_ix_i'(X'X)^{-1}}{1 - h_i}$$

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# Proof of 5.5

Continuing from above:

$$\hat{\beta}_{i} = (X'_{i}X_{i})^{-1}(X'Y - x_{i}y_{i})$$

$$= \left[ (X'X)^{-1} + \frac{(X'X)^{-1}x_{i}x'_{i}(X'X)^{-1}}{1 - h_{i}} \right] (X'Y - x_{i}y_{i})$$

$$= (X'X)^{-1}X'Y - (X'X)^{-1}x_{i}y_{i} + \frac{(X'X)^{-1}x_{i}x'_{i}X'Y}{1 - h_{i}} - \frac{(X'X)^{-1}x_{i}x'_{i}x_{i}y_{i}}{1 - h_{i}}$$

$$= \hat{\beta} - \frac{(X'X)^{-1}x_{i}}{1 - h_{i}} \left[ y_{i}(1 - h_{i}) - x_{i}\hat{\beta} + h_{i}y_{i} \right]$$

$$= \hat{\beta} - \frac{(X'X)^{-1}x_{i}}{1 - h_{i}} \left[ y_{i} - x_{i}\hat{\beta} \right]$$

$$= \hat{\beta} - \frac{(X'X)^{-1}x_{i}r_{i}}{1 - h_{i}}$$

$$\hat{\beta} - \hat{\beta}_{i} = \frac{(X'X)^{-1}x_{i}r_{i}}{1 - h_{i}}$$

I found this proof to be tricky, so I spent a lot of time reading through linear algebra/linear regression texts. In particular Linear Regression Analysis by Seber and Lee (2003), especially Chapter 10, we really helpful in helping me complete these proofs.