1. Consider the 1996 American National Election Study data. The response is "sPID" that can be Democrat, Independent, or Republican. We consider the effect from "nin-come" (continuous variable in \$1000). Below is the summary of the fit of a multinomial regression model with the variable "nincome" only.

```
mmodi <- multinom(sPID ~ nincome, nes96)</pre>
summary(mmodi)
# Call:
# multinom(formula = sPID ~ nincome, data = nes96)
# Coefficients:
            # (Intercept)
                              nincome
# Independent -1.1749331 0.01608683
# Republican
               -0.9503591 0.01766457
# Std. Errors:
            # (Intercept)
                               nincome
# Independent
                0.1536103 0.002849738
# Republican
                0.1416859 0.002652532
# Residual Deviance: 1985.424
# AIC: 1993.424
```

- (a) (5 points) Provide the interpretation of the coefficient -1.1749331 under "(Intercept)".
- (b) (5 points) Provide the interpretation of the coefficient 0.01766457 under "nincome".
- (c) (10 points) Provide the predicted proportions of each category when the value of "nincome" is 42.
- (d) (5 points) Suppose we fit instead with the following code:

polr(formula = sPID ~ nincome, data = nes96)

How many coefficients (including intercept) will be in the output?

2. (20 points) Suppose $\mathbf{X} = (X_1, \dots, X_p)$ and $Y \in \{0, 1\}$. We want to choose a decision function $h(\mathbf{X})$ to minimize the risk according to the 0 - 1 loss Function:

$$\mathcal{L}(y, h(\boldsymbol{X})) = \mathbf{I}(y \neq h(\boldsymbol{X})),$$

where I is the indicator function. With this loss function, the risk is

$$\mathcal{R}(h) = \mathbb{E}[\mathcal{L}(y, h(\boldsymbol{X}))] = \mathbb{P}(y \neq h(\boldsymbol{X})).$$

Show that the minimizer of $\mathcal{R}(h)$ is

$$h^*(\boldsymbol{x}) = \left\{ \begin{array}{ll} 1 & \mathrm{P}(y=1|\boldsymbol{X}=\boldsymbol{x}) \geq 1/2 \\ 0 & \mathrm{otherwise} \end{array} \right.$$

3. Consider the GLM with

$$f(y_i|\theta) = exp\left\{\frac{1}{a_i(\phi)}(y_i\theta - b(\theta)) + c(y_i, \phi)\right\}$$
(1)

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and with linear predictors $\eta_i = \boldsymbol{x}_i^T \boldsymbol{\beta}, i = 1, \dots, n$. Suppose ϕ is known and \boldsymbol{x} are fixed.

- (a) (30 points) Suppose we use the canonical link function. Show that in the MLE of β , the Fisher Scoring algorithm can be implemented by IRLS.
- (b) (15 points) Show that the equivalence of Fisher Scoring algorithm and IRLS is generally true for any proper link function $g(\cdot)$.
- (c) (10 points) When the IRLS converges, why shouldn't we use the SE estimates of β from the LS fit in the last step? How to correctly estimate the SEs?