

STAT 30850 Homework 4

Sarah Adilijrang

Problem 1: Randomized Inference

- (a) Given a fixed feature vector $X_i : Y_i \sim \text{Binomial}(n_i, f(x_i))$ where $f(x_i) = \lambda(x_i^T \beta)$
- $$\Rightarrow P(Y_i = y_i | X_i) = \binom{n_i}{y_i} f(x_i)^{y_i} (1 - f(x_i))^{n_i - y_i}$$

For each i , draw $Z_i \sim \text{Binomial}(Y_i, \lambda)$ where $\lambda \in (0, 1)$

$$\Rightarrow P(Z_i = z_i | Y_i = y_i) = \binom{y_i}{z_i} \lambda^{z_i} (1 - \lambda)^{y_i - z_i}, \text{ where } z_i \leq y_i \leq n_i$$

$$\begin{aligned} \Rightarrow P(Z_i = z_i | X_i) &= \sum_{y_i=0}^{n_i} P(Z_i = z_i | Y_i = y_i) \cdot P(Y_i = y_i | X_i) \\ &= \sum_{y_i=z_i}^{n_i} \binom{y_i}{z_i} \lambda^{z_i} (1 - \lambda)^{y_i - z_i} \cdot \binom{n_i}{y_i} f(x_i)^{y_i} (1 - f(x_i))^{n_i - y_i} \\ &= \sum_{y_i=z_i}^{n_i} \frac{y_i!}{z_i!(n_i - z_i)!} \lambda^{z_i} (1 - \lambda)^{y_i - z_i} \frac{n_i!}{y_i!(n_i - y_i)!} f(x_i)^{y_i} f(x_i)^{z_i} (1 - f(x_i))^{n_i - y_i - z_i} \\ &\stackrel{\text{set } m_i = y_i - z_i}{=} \frac{n_i!}{z_i!(n_i - z_i)!} (\lambda f(x_i))^{z_i} \sum_{m_i=0}^{n_i - z_i} \frac{(n_i - z_i)!}{m_i!(n_i - z_i - m_i)!} ((1 - \lambda)f(x_i))^{m_i} (1 - f(x_i))^{n_i - z_i - m_i} \\ &= \binom{n_i}{z_i} (\lambda f(x_i))^{z_i} [(\lambda f(x_i)) + (1 - \lambda f(x_i))]^{n_i - z_i} \\ &= \binom{n_i}{z_i} (\lambda f(x_i))^{z_i} (1 - \lambda f(x_i))^{n_i - z_i} \end{aligned}$$

$$\Rightarrow Z_i | X_i \sim \text{Binomial}(n_i, \lambda f(x_i))$$

$$\begin{aligned} (b) P(Y_i | X_i, Z_i) &= \frac{P(Z_i | Y_i, X_i) \cdot P(Y_i | X_i)}{P(X_i)} = \frac{P(Z_i | Y_i) \cdot P(Y_i | X_i) P(X_i)}{P(Z_i | X_i) P(X_i)} = \frac{P(Z_i | Y_i) \cdot P(Y_i | X_i)}{P(Z_i | X_i)} \\ &= \frac{\binom{y_i}{z_i} \lambda^{z_i} (1 - \lambda)^{y_i - z_i} \cdot \binom{n_i}{y_i} f(x_i)^{y_i} (1 - f(x_i))^{n_i - y_i}}{\binom{n_i}{z_i} (\lambda f(x_i))^{z_i} (1 - \lambda f(x_i))^{n_i - z_i}} \\ &= \frac{\binom{n_i}{z_i} (\lambda f(x_i))^{z_i} \cdot \binom{n_i - z_i}{y_i - z_i} ((1 - \lambda)f(x_i))^{y_i - z_i} (1 - f(x_i))^{n_i - y_i}}{\binom{n_i}{z_i} (\lambda f(x_i))^{z_i} \cdot (1 - \lambda f(x_i))^{n_i - z_i}} \\ &= \binom{n_i - z_i}{y_i - z_i} \left[\frac{((1 - \lambda)f(x_i))^{y_i - z_i}}{1 - \lambda f(x_i)} \right] \left[\frac{(1 - f(x_i))^{n_i - y_i}}{1 - f(x_i)} \right] \end{aligned}$$

$$\Rightarrow Y_i | X_i, Z_i \sim \text{Binomial}\left(n_i - z_i, \frac{(1 - \lambda)f(x_i)}{1 - \lambda f(x_i)}\right)$$

(C) $Z_i \sim \text{Binomial}(Y_i, \lambda)$, where $\lambda \in (0, 1)$ represents the chance of being recorded for the exploratory data
 Since $Z_i | X_i \sim \text{Binomial}(n_i, \lambda f(x_i))$ & $Y_i | X_i, Z_i \sim \text{Binomial}(n_i - z_i, \frac{(1-\lambda)f(x_i)}{1-\lambda f(x_i)})$

$\Rightarrow \begin{cases} \text{the probability } \lambda f(x_i) \text{ is a monotone increasing function of } \lambda \\ \text{the probability } \frac{(1-\lambda)f(x_i)}{1-\lambda f(x_i)} = 1 - \frac{1-f(x_i)}{1-\lambda f(x_i)} \text{ is a monotone decreasing function of } \lambda \end{cases}$

$\therefore \lambda \in (0, 1) \therefore \lambda f(x_i) \in (0, f(x_i)) \text{ & } \frac{(1-\lambda)f(x_i)}{1-\lambda f(x_i)} \in (f(x_i), 0)$

① When λ is large, i.e. $\lambda \rightarrow 1$:

$$\begin{cases} Z_i \sim \text{Binomial}(Y_i, \lambda \rightarrow 1) \Rightarrow Z_i \text{ would be close to } Y_i \\ \lambda f(x_i) \rightarrow f(x_i) \Rightarrow Z_i | X_i \sim \text{Binomial}(n_i, p \rightarrow f(x_i)) \Rightarrow E(Z_i | X_i) \approx n_i f(x_i) \\ \frac{(1-\lambda)f(x_i)}{1-\lambda f(x_i)} \rightarrow 0 \Rightarrow Y_i | X_i, Z_i \sim \text{Binomial}(n_i - z_i, p \rightarrow 0) \end{cases}$$

② When λ is small, i.e. $\lambda \rightarrow 0$:

$$\begin{cases} Z_i \sim \text{Binomial}(Y_i, \lambda \rightarrow 0) \Rightarrow Z_i \text{ would be close to } 0 \\ \lambda f(x_i) \rightarrow 0 \Rightarrow Z_i | X_i \sim \text{Binomial}(n_i, p \rightarrow 0) \\ \frac{(1-\lambda)f(x_i)}{1-\lambda f(x_i)} \rightarrow f(x_i) \Rightarrow Y_i | X_i, Z_i \sim \text{Binomial}(n_i - z_i, p \rightarrow f(x_i)) \Rightarrow E(Y_i | X_i, Z_i) \approx (n_i - z_i) f(x_i) \approx n_i f(x_i) \end{cases}$$

Note that in both ① & ②, we can estimate $\hat{f}(x_i) = \frac{\hat{Y}_i}{n_i}$ ($i=1, \dots, n$) thus get the estimate of function $f(\cdot)$

Problem 2: Conformal Prediction

Assume $(X_1, Y_1), \dots, (X_n, Y_n), (X_{n+1}, Y_{n+1})$ are iid

Now we need to look for values y , s.t. in the data set $(X_1, Y_1), \dots, (X_n, Y_n), (X_{n+1}, Y_{n+1})$, the last point (X_{n+1}, y) does not appear "unusual" relative to the others

Thus we train the KNN model on the data set $(X_1, Y_1), \dots, (X_n, Y_n), (X_{n+1}, Y_{n+1})$:

For each (X_i, Y_i) , suppose X_{i_1}, \dots, X_{i_k} ($i_1, \dots, i_k \neq i$) are k nearest neighbors of X_i ($i=1, \dots, n, n+1$)

$$\Rightarrow \hat{P}_i = \frac{1}{k} \sum_{i=1}^k Y_{i_z}, \text{ where } Y_{i_z} = \begin{cases} Y_{i_z} & \text{if } i_z = 1, \dots, n \\ y & \text{if } i_z = n+1 \end{cases}$$

$$\Rightarrow \text{Residuals} = R_i^y = \begin{cases} |Y_i - \hat{P}_i| & \text{if } i=1, \dots, n \\ |y - \hat{P}_{n+1}| & \text{if } i=n+1 \end{cases}$$

\Rightarrow The Prediction Interval for Y_{n+1} is:

$$\{y \in \mathbb{R} : R_{n+1}^y \leq [(1-\alpha)(n+1)]\text{-th smallest value of } R_1^y, \dots, R_n^y, R_{n+1}^y\}$$