

Gordon Ng CS 505 Homework

(k) Y is boolean

$$X = \{X_1, X_2, \dots, X_n\}$$

For X_i , $P(X_i | Y = y_k)$ is Gaussian/Normal distribution

Every X_i and X_j , $i \neq j$ are conditionally independent

$$P(Y=1|X) = \frac{P(Y=0) \prod_i P(X_i | Y=0)}{P(Y=0) \prod_i P(X_i | Y=0) + P(Y=1) \prod_i P(X_i | Y=1)}$$

$$P(Y=1|X) = \frac{1}{1 + \exp(\ln \frac{1-\pi}{\pi} + \sum_i \ln \frac{P(X_i | Y=0)}{P(X_i | Y=1)})}$$

We turn the summation to Gaussian form.

$$P(Y=1|X) = \frac{1}{1 + \exp(\ln \frac{1-\pi}{\pi} + \sum_i (\frac{\mu_{i0} - \mu_{i1}}{\sigma_i^2} X_i + \frac{\mu_{i1}^2 - \mu_{i0}^2}{2\sigma_i^2}))}$$

Set the weighted sums to w_0 and w_i

$$w_0 = \ln \frac{1-\pi}{\pi} + \sum_i \frac{\mu_{i1}^2 - \mu_{i0}^2}{2\sigma_i^2} \quad w_i = \frac{\mu_{i0} - \mu_{i1}}{\sigma_i^2}$$

$$P(Y=0|X) = 1 - P(Y=1|X) = \frac{\exp(w_0 + \sum_{i=1}^n w_i X_i)}{1 + \exp(w_0 + \sum_{i=1}^n w_i X_i)}$$

Conditional Data Likelihood Log Regression Parameter

$$W \leftarrow \arg \max_W \prod P(Y^i | X^i; W)$$

$$l(W) = \sum_i (Y^i \ln P(Y^i=1 | X^i, W) + (1-Y^i) \ln P(Y^i=0 | X^i, W))$$

$$= \sum_i Y^i (w_0 + \sum_{i=1}^n w_i X_i) - \ln(1 + \exp(w_0 + \sum_{i=1}^n w_i X_i))$$

No closed form to maximize $l(W)$, so gradient descent ascent

$$\frac{\partial l(W)}{\partial w_i} = \sum_i X_i^i (Y^i - \hat{P}(Y^i=1 | X^i, W))$$

You can plug in $P(Y=0|X)$ to form a Log Regression.

$$1) 2. Y: \text{Sentiment} \in \{0, 1\}$$

$$P(\text{Sentiment} = 1) = 0.5$$

$$X_1: \text{Summer} \in \{0, 1\}$$

$$P(\text{Summer} = 1 | \text{Sentiment} = 1) = 0.8$$

$$X_2: \text{Rowdy} \in \{0, 1\}$$

$$P(\text{Summer} = 1 | \text{Sentiment} = 0) = 0.7$$

$$P(\text{Rowdy} = 1 | \text{Sentiment} = 1) = 0.4$$

$$P(\text{Rowdy} = 1 | \text{Sentiment} = 0) = 0.5$$

$$a) \text{ decision function } f(x_1, x_2) = 1$$

$$\text{if } P(Y=1 | x_1, x_2) > P(Y=0 | x_1, x_2)$$

$$Y=1 \text{ if: } \frac{\log P(Y=1)}{\log P(Y=0)} + \frac{\log P(X_1=x_1 | Y=1)}{\log P(X_1=x_1 | Y=0)} + \frac{\log P(X_2=x_2 | Y=1)}{\log P(X_2=x_2 | Y=0)} > 0 \text{ else } Y=0$$

$$b) \begin{matrix} x_1 & x_2 & Y \end{matrix}$$

$$X_1 = \text{Summer}$$

$$1 \quad 0$$

$$1$$

$$X_2 = \text{Rowdy}$$

$$0 \quad 1$$

$$0$$

$$0 \quad 0 \quad 0$$

$$E_e = \sum_{i \in \{0,1\}} \sum_{j \in \{0,1\}} \sum_{k \in \{0,1\}} P(X_1=i, X_2=j, Y=k) \cdot I[k \neq \text{NB-Prediction}(X_1=i, X_2=j)]$$

$$I[z] \text{ is an indicator function, where } I[z]=1 \text{ or } I[z]=0$$

$$E_e = P(X_1=0, Y=1) + P(X_1=1, Y=0) = P(Y=1)P(X_1=0 | Y=1) + P(Y=0)P(X_1=1 | Y=0)$$

$$E_e = 0.5 \times 0.7 + 0.5 \times 0.5$$

$$\text{For } x_1 \quad E_e = 0.5 \times 0.2 + 0.5 \times 0.7 = 0.1 + 0.35 = 0.45$$

$$\text{For } x_2 \quad E_e = 0.5 \times 0.6 + 0.5 \times 0.5 = 0.6 + 0.25 = 0.85$$

$$\text{For 1 attribute } P(X_1, X_2, Y) = P(Y)P(X_1 | Y)P(X_2 | Y)$$

$$E_e = P(X_1=1, X_2=1, Y=0) + P(X_1=1, X_2=0, Y=0) +$$

$$P(X_1=0, X_2=1, Y=0) + P(X_1=0, X_2=0, Y=1)$$

$$E_e = 0.5 \times 0.7 \times 0.5 + 0.5 \times 0.7 \times 0.5 + 0.5 \times 0.3 \times 0.5 + 0.5 \times 0.2 \times 0.6$$

$$E_e = 0.485$$

$$c) P(X_1=1, X_2=1, Y=1)$$

$$P(X_1 | Y) \quad P(X_2 | Y)$$

$$P(X_1=1 | Y=1) = \frac{P(Y | X_1) \cdot P(X_1)}{P(Y)}$$

$$P(X_2=1 | Y=1) = \frac{P(Y | X_2) \cdot P(X_2)}{P(Y)}$$

$$P(Y | X_1) \cdot P(X_1) = 0.5 \times 0.8 = .4$$

$$P(Y | X_2) \cdot P(X_2) = 0.4 \times 0.5 = .2$$

$$\frac{\log(X_1 | Y=1)}{\log(X_1 | Y=0)} = 0.62562$$

$$\frac{\log(X_2 | Y=1)}{\log(X_2 | Y=0)} = 1.32192$$

$$\log(X_1 | Y=0)$$

$$\log(X_2 | Y=0)$$

$$P(X_1) = 0.63936$$

$$P(X_2) = 0.15129$$

$$P(X_1, X_2, Y) = 0.5 \times 0.63936 \times 0.15129$$

$$0.048364872$$

1) 2d) The NB assumptions are violated because the attributes are supposed to be conditionally independent, but $X_2 = \text{Winter}$ is not independent. The ~~joint~~ joint probability should be the same as $P(Y=1, X_1, X_2)$. Winter is just another season, two seasons can't happen at once. So, 0.04836.43872.

2e) The expected error rate is higher.

$$X_1 = 1 \cap X_2 = 1 \mid Y = 1$$

$$X_1 = 1 \cap X_2 = 0 \mid Y = 1$$

$$X_1 = 0 \cap X_2 = 1 \mid Y = 0$$

$$X_1 = 0 \cap X_2 = 0 \mid Y = 0$$

$$P(X_1=1, X_2=1, Y=0) + P(X_1=1, X_2=0, Y=0) + P(X_1=0, X_2=1, Y=1) + P(X_1=0, X_2=0, Y=1)$$

$$P(X_1, X_2, Y) = P(Y) P(X_1|Y) P(X_2|Y)$$

$$0.5 \times 0.5 \times 0.5 + 0.5 \times 0.5 \times 0.7 + 0.2 \times 0.5 \times 0.4 + 0.2 \times 0.6 \times 0.5$$

$$0.175 + 0.175 + 0.04 + 0.06 = 0.45 = E_e$$

2f) It doesn't improve because we did not provide new information as Winter and Summer are both seasons. Adding more attributes will only make the Expected error go up, as we saw here. (question 2c-2e)

3a) These words will receive zero probability in maximum likelihood estimates. This zero probability is still there even after the event, so it will mess up your data.

3b) Logistic regression will use parameters of logit/regression functions not estimates of $P(Y)$ and $P(X|Y)$.

$$w_j := w_j + \eta \frac{\partial}{\partial w_j} l(w)$$

The weight is calc using gradient descent and all weights are simultaneously updated. It uses a logit function.