DATS 6202 Term 2018-Fall

Machine Learning I

Quiz 2 September 25, 2018

Quiz 2: Solutions

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Material Covered

• Logistic regression

Note

- The quiz has 100 points.
- The quiz period is 20 minutes.
- The quiz is closed book and closed notes.
- The quiz is closed electronics (e.g., no laptops, netbooks, OLPCs, tablets, iPads, calculators, cellular phones, iPhones, Nexi, iPods, Zunes, Kindles, Nooks).
- There is only one correct answer for each Multiple Choice Question.
- For each Calculation question (if there is any), you must show the essential steps. **No mark will be given if only the result is provided**.

1 Multiple Choice Questions (20 points)

- 1. Which of the following claim is correct about the logit function?
 - (a) logit(P) = log(odds(P))
 - (b) logit(P) = odds(log(P))

a

- 2. Which of the following claim is correct about the logistic regression model?
 - (a) The parameters can be estimated by maximizing the joint likelihood (the objective function)
 - (b) The parameters can be estimated by minimizing the joint likelihood (the objective function)

a

2 Description and Calculation (80 points)

The logistic regression model can be written as

$$p(y|\mathbf{X}) = \frac{1}{1 + e^{-z}} \quad \text{where} \quad z = \sum_{j=0}^{d} \mathbf{w}_{j}(y) \cdot \mathbf{x}_{j}. \tag{1}$$

Here,

- y is a class label (e.g., High, Normal, or Low)
- X is the feature vector
- $p(y|\mathbf{X})$ is the probability of y given \mathbf{X}
- d is the number of features
- \mathbf{x}_j is the jth feature (where the dummy feature, \mathbf{x}_0 , is always 1)
- $w_j(y)$ is the weight of x_j with respect to class label y

The rule for updating $w_j(y)$ (where $0 \le j \le d$) can be written as

$$\mathbf{w}_{j}(y) = \mathbf{w}_{j}(y) + \Delta \mathbf{w}_{j}(y) \quad \text{where} \quad \Delta \mathbf{w}_{j}(y) = \sum_{i=1}^{n} \eta \cdot \left(f(y_{i}, y) - P(y | \mathbf{X}_{i}) \right) \cdot \mathbf{x}_{j}.$$
 (2)

Here,

- $\Delta w_j(y)$ is the update of $w_j(y)$
- n (above the \sum symbol) is the number of samples
- η is the learning rate
- y_i is the actual class label of sample i
- y is the predicted class label of sample i (using eq. (1))
- $f(y_i, y)$ is the indicator function, which indicates whether our prediction is correct (i.e., $y_i = y$). That is, $f(y_i, y)$ is 1 when $y_i = y$ and 0 otherwise:

$$f(y_i, y) = \begin{cases} 1, & \text{if } y_i = y \\ 0, & \text{otherwise} \end{cases}$$
 (3)

- X_i is the feature vector of sample i
- $p(y|\mathbf{X}_i)$ is the probability of y given \mathbf{X}_i
- $f(y_i, y) P(y|\mathbf{X}_i)$ is the error for sample i

1. Explain why η cannot be zero.

If η were zero, $\Delta w_i(y)$ would always be zero. As a result, $w_i(y)$ would not be updated.

- 2. Explain why η cannot be negative. You should demonstrate that, if η were negative then the updating rule would increase (rather than decrease) the error. You should rely on the following assumption when making your argument.
 - $f(y_i, y) P(y|\mathbf{X}_i) > 0$ (i.e., the error for sample i is positive)
 - $\mathbf{x}_i > 0$ (i.e., the feature is always positive)

If η were negative, $\Delta w_j(y)$ for sample i would be negative (since the assumption says that both the error and the feature is positive). In turn, $w_j(y)$ would be decreased (based on eq. (2)). Next, first z then $p(y|\mathbf{X})$ would be decreased (based on eq. (1)). Finally the error would be increased.

3. Assume there is one feature x_1 and three class labels (High, Normal, Low) in the data. The parameter values (with respect to each class label) obtained by eq. (2) are as follows:

$$w_0(\text{High}) = -1 \quad \text{and} \quad w_1(\text{High}) = 1 \tag{4}$$

$$w_0(\text{Normal}) = 1$$
 and $w_1(\text{Normal}) = -1$ (5)

$$w_0(\text{Low}) = 10$$
 and $w_1(\text{Low}) = 10$ (6)

Now given a new sample where $x_1 = 1$:

• calculate the following probabilities using eq. (1) (where you may assume $e^{-20} \approx 0$):

$$P(\text{High}|\mathbf{x}_1 = 1) \tag{7}$$

$$\begin{split} P(\mathrm{High}|\mathbf{x}_1 = 1) &= \frac{1}{1 + e^{-w_0(\mathrm{High}) - w_1(\mathrm{High}) \times \mathbf{x}_1}} \\ &= \frac{1}{1 + e^{1 - 1 \times 1}} \\ &= 0.5 \end{split}$$

$$P(\text{Normal}|\mathbf{x}_1 = 1) \tag{8}$$

$$\begin{split} P(\text{Normal}|\mathbf{x}_1 = 1) &= \frac{1}{1 + e^{-w_0(\text{Normal}) - w_1(\text{Normal}) \times \mathbf{x}_1}} \\ &= \frac{1}{1 + e^{-1 + 1 \times 1}} \\ &= 0.5 \end{split}$$

$$P(\text{Low}|\mathbf{x}_1 = 1) \tag{9}$$

$$P(\text{Low}|\mathbf{x}_1 = 1) = \frac{1}{1 + e^{-w_0(\text{Low}) - w_1(\text{Low}) \times \mathbf{x}_1}}$$
$$= \frac{1}{1 + e^{-10 - 10 \times 1}}$$
$$\approx 1$$

• based on the probabilities above, what is the predicted class label? why?

The predicted class label is Low, since it has the largest probability.

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(You may use it as scratch paper, but do submit it as part of your completed exam.)