Natural Language Processing

Tutorial 6 (Week 9): ML & DL

Imagine you're working on a basic sentiment analysis task. You have collected a small dataset where each data point consists of the number of positive words in a movie review and the corresponding rating given by the reviewer on a scale of 1 to 10. Now use a simple linear regression model to predict the movie rating based on the number of positive words. Your model should be defined as: y = wx + b, where x = number of positive words.

Use the following data to derive

(1) The optimal weight w and bias b using the least squares method.

Number of Positive Words	Movie Rating
1	3
3	6
5	8
6	9

$$egin{aligned} J(w,b) &= \sum_i (y_i - \hat{y}_i)^2 \ &= \sum_i (y_i - (wx_i + b))^2 \end{aligned}$$

This is convex, compute partial derivatives and equate to 0

$$egin{aligned} rac{\partial J}{\partial w} &= -2\sum_i x_i(y_i - (wx_i + b)) = 0 \ rac{\partial J}{\partial b} &= -2\sum_i (y_i - (wx_i + b)) = 0 \end{aligned}$$

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Rearrange the above equations to get

$$egin{aligned} \sum_i x_i y_i &= w \sum_i x_i^2 + b \sum_i x_i - \ \sum_i y_i &= w \sum_i x_i + n b \end{aligned}$$

Rearrange the above equations to get

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Solving this system of 2 equations over 2 variables, we get

$$w=rac{n\sum_i x_i y_i - \sum_i x_i \sum_i y_i}{n\sum_i x_i^2 - \left(\sum_i x_i
ight)^2} \quad b=rac{\sum_i y_i - w \sum_i x_i}{n}$$

Solving this system of 2 equations over 2 variables, we get

$$w=rac{n\sum_{i}x_{i}y_{i}-\sum_{i}x_{i}\sum_{i}y_{i}}{n\sum_{i}x_{i}^{2}-\left(\sum_{i}x_{i}
ight)^{2}}\quad b=rac{\sum_{i}y_{i}-w\sum_{i}x_{i}}{n}}{y_{i}}$$

Now plug in the values from the table

$$n = 4$$

<i>U</i>	
Number of Positive Words	Movie Rating
1	3
3	6
5	8
6	9

$$w=rac{n\sum_{i}x_{i}y_{i}-\sum_{i}x_{i}\sum_{i}y_{i}}{n\sum_{i}x_{i}^{2}-\left(\sum_{i}x_{i}
ight)^{2}}$$

$$b = rac{\sum_i y_i - w \sum_i x_i}{n}$$

$$w=rac{4(13+36+58+69)-(1+3+5+6)(3+6+8+9)}{4(1+9+25+36)-(1+3+5+6)^2} \ pprox 1.2$$

$$b=rac{(3+6+8+9)-1.2(1+3+5+6)}{4}=2$$

Now plug in the values from the table

$$n = 4$$

x_i	
Number of Positive Words	Movie Rating
1	3
3	6
5	8
6	9

Use the following data to derive

(2) Once you have the parameters, what would be the predicted rating for a review with 4 positive words?

Number of Positive Words	Movie Rating
1	3
3	6
5	8
6	9

$$x = 4, w = 1.2, b = 2, y = ?$$

Number of Positive Words	Movie Rating
1	3
3	6
5	8
6	9

$$x = 4, w = 1.2, b = 2, y = ?$$
 $y = wx + b = 1.2 \times 4 + 2 \approx 7$

Number of Positive Words	Movie Rating
1	3
3	6
5	8
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You're trying to predict whether a student will pass or fail an upcoming exam based on the number of hours they've studied. You have the

following data:

Hours studied (x)	Pass (1) or Fail (0)
1	0
2	0
4	1
5	1

(1) Write the logistic regression function given the input x.

• The logistic function can be written as the sigmoid function:

$$\sigma(z)=rac{1}{1+e^{-z}} \qquad z=wx+b$$

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4	1
5	1

(2) Compute the logistic loss for the first data point (x=1, y=0) given that w=1 and b=-3.

- ullet Given w=1, b=-3, we can have z=wx+b=1 imes 1-3=-2
- The predicted output becomes: $\hat{y} = \sigma(-2) = \frac{1}{1+e^2}$
- According to the logistic loss function:

$$L(y, \hat{y}) = -y \log \hat{y} - (1 - y) \log(1 - \hat{y})$$

Plug in the values to obtain

$$L(0,\hat{y}) = -\log(1-\hat{y}) = -\lograc{e^2}{1+e^2}$$

You're trying to predict whether a student will pass or fail an upcoming exam based on the number of hours they've studied. You have the following data:

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4	1
5	1

(3) Derive the gradient of the logistic loss with respect to w and b. Then compute the gradient for the first data point using the same w and b values.

Enumerate the entire forward process

$$egin{aligned} z &= wx + b \ \hat{y} &= \sigma(z) \ L(y,\hat{y}) &= -y\log\hat{y} - (1-y)\log(1-\hat{y}) \end{aligned}$$

Use chain rule

$$\frac{\partial L}{\partial w} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial z} \frac{\partial z}{\partial w}$$

According to the logistic loss function:

$$L(y,\hat{y}) = -y\log\hat{y} - (1-y)\log(1-\hat{y})$$

ullet The gradient wrt $\,\hat{y}$

$$rac{\partial L}{\partial \hat{y}} = -rac{y}{\hat{y}} + rac{(1-y)}{1-\hat{y}}$$

• The gradient wrt \hat{y} $\frac{\partial L}{\partial \hat{y}} = -\frac{y}{\hat{y}} + \frac{(1-y)}{1-\hat{y}}$

• The gradient wrt z

$$\hat{y} = rac{1}{1 + e^{-z}} \qquad rac{\partial \hat{y}}{\partial z} = -rac{-1 imes e^{-z}}{(1 + e^{-z})^2} = rac{e^{-z}}{(1 + e^{-z})^2}$$

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ight)^2} = rac{e^{-z}}{\left(1 + e^{-z}
ight)^2}$$

• The gradient wrt w $\frac{\partial z}{\partial w} = x$

Applying chain rule

$$\begin{aligned} \frac{\partial L}{\partial \hat{y}} &= -\frac{y}{\hat{y}} + \frac{(1-y)}{1-\hat{y}} \begin{vmatrix} \frac{\partial \hat{y}}{\partial z} &= -\frac{1\times e^{-z}}{(1+e^{-z})^2} = \frac{e^{-z}}{(1+e^{-z})^2} \end{vmatrix} \frac{\partial z}{\partial w} = x \\ \frac{\partial L}{\partial w} &= \frac{\partial L}{\partial y} \frac{\partial y}{\partial z} \frac{\partial z}{\partial w} = \left(-\frac{y}{\hat{y}} + \frac{(1-y)}{1-\hat{y}} \right) \frac{e^{-z}}{(1+e^{-z})^2} x \\ &= -\frac{ye^{-z}}{1+e^{-z}} x + \frac{1-y}{1+e^{-z}} x = \frac{-yx(1+e^{-z})+x}{1+e^{-z}} \\ &= -yx + \frac{x}{1+e^{-z}} = (\hat{y} - y)x \end{aligned}$$

ullet The gradient wrt w is $rac{\partial L}{\partial w}=rac{\partial L}{\partial y}rac{\partial y}{\partial z}rac{\partial z}{\partial w}=(\hat{y}-y)x$

Similarly, the gradient wrt b is

$$\frac{\partial L}{\partial b} = \frac{\partial L}{\partial y} \frac{\partial y}{\partial z} \frac{\partial z}{\partial b} = (\hat{y} - y)$$

• The gradient for the first data point (x=1, y=0) is

$$rac{\partial L}{\partial w} = rac{\partial L}{\partial y} rac{\partial y}{\partial z} rac{\partial z}{\partial w} = (\hat{y} - y)x = (\hat{y} - 0) imes 1 = rac{1}{1 + e^2}$$

$$rac{\partial L}{\partial b} = rac{\partial L}{\partial y} rac{\partial y}{\partial z} rac{\partial z}{\partial b} = (\hat{y} - y) = rac{1}{1 + e^2}$$

Coding Practice

- Linear Regression:
 https://colab.research.google.com/drive/12QpBf7x_Jt6-zypN4OrUFFHXz1u6CmYe?usp=sharing
- Logistic Regression:
 https://colab.research.google.com/drive/lnTrYW5dUu6WO9cx7SGEvP9oX7qRbsGJk?usp=s
 https://colab.research.google.com/drive/lnTrYW5dUu6WO9cx7SGEvP9oX7qRbsGJk?usp=s
 https://colab.research.google.com/drive/lnTrYW5dUu6WO9cx7SGEvP9oX7qRbsGJk?usp=s