

Weekly Report 1-Logistic Regression

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Introduction

Logistic regression is a misnomer since it is a classification algorithm. Unlike linear regression which outputs continuous number values, logistic regression transforms its output using the logistic sigmoid function to return a probability value which can then be mapped to two or more discrete classes.

Algorithm

We try to fit the data into a curved 'S' like graph unlike the straight line graph in linear regression.

The name of the algorithm comes from the function which is used to transform its output to return a probability value which can then be mapped to two or more discrete classes.

We assume functional form of $P(Y|X)$ and estimate parameters of $P(Y|X)$ directly from training data.

Let $p_y(x; w)$ be our estimate of $P(Y|X)$, where \mathbf{w} is a vector of adjustable parameters.

$$P(Y = 1|X, \mathbf{w}) = \frac{1}{1 + \exp(-\mathbf{w}^\top X)} \quad (1)$$

In case of binary class problem, log odds of y or logit transformation of y is a linear function of x .

Inverse of logit is the Logistic function which is sigmoid function for binary class problem. We estimate \mathbf{w} using maximum likelihood estimation.

$$\mathbf{w} = \arg \max_{\mathbf{w}} \sum_l \ln P(y^l | \mathbf{x}^l, \mathbf{w}) \quad (2)$$

This involves minimising negative likelihood which is convex.

We use gradient descent for the minimisation problem by updating the weights in the direction of gradient.

Key points

- It does not assume on $P(X|Y)$ and learns the parameters that maximises the conditional probability $P(Y|X)$.
- It is a discriminative model which draws boundaries in the data space and focusses on predicting the labels.
- After predicting the probabilities of the output belong to a class, we need to map the probabilities to classes by using the decision threshold.
- It is a linear classifier as the decision rule is hyperplane.
- Softmax activation is used for multi class logistic regression.

Figure 1: Algorithm for binary class gradient descent(Logistic Regression)

```
For  $j = 0, \dots, d$   
   $w_j \leftarrow \text{rand}(-0.01, 0.01)$   
Repeat  
  For  $j = 0, \dots, d$   
     $\Delta w_j \leftarrow 0$   
  For  $t = 1, \dots, N$   
     $o \leftarrow 0$   
    For  $j = 0, \dots, d$   
       $o \leftarrow o + w_j x_j^t$   
     $y \leftarrow \text{sigmoid}(o)$   
    For  $j = 0, \dots, d$   
       $\Delta w_j \leftarrow \Delta w_j + (r^t - y) x_j^t$   
  For  $j = 0, \dots, d$   
     $w_j \leftarrow w_j + \eta \Delta w_j$   
Until convergence
```

Figure 2: Algorithm for multi class gradient descent(Logistic Regression)

```

For  $i = 1, \dots, K$ 
  For  $j = 0, \dots, d$ 
     $w_{ij} \leftarrow \text{rand}(-0.01, 0.01)$ 
Repeat
  For  $i = 1, \dots, K$ 
    For  $j = 0, \dots, d$ 
       $\Delta w_{ij} \leftarrow 0$ 
  For  $t = 1, \dots, N$ 
    For  $i = 1, \dots, K$ 
       $o_i \leftarrow 0$ 
      For  $j = 0, \dots, d$ 
         $o_i \leftarrow o_i + w_{ij}x_j^t$ 
      For  $i = 1, \dots, K$ 
         $y_i \leftarrow \exp(o_i) / \sum_k \exp(o_k)$ 
      For  $i = 1, \dots, K$ 
        For  $j = 0, \dots, d$ 
           $\Delta w_{ij} \leftarrow \Delta w_{ij} + (r_i^t - y_i)x_j^t$ 
    For  $i = 1, \dots, K$ 
      For  $j = 0, \dots, d$ 
         $w_{ij} \leftarrow w_{ij} + \eta \Delta w_{ij}$ 
Until convergence

```

```

1
2 class LogisticRegression():
3     def __init__(self, w, learning_rate, num_epochs):
4         self.w = w
5         self.learning_rate = learning_rate
6         self.num_epochs = num_epochs
7
8     def sigmoid(self, x):
9         return 1/(1 + np.exp(-x))
10
11    def train(self, X, y):
12        n, m = X.shape
13
14
15        for epoch in range(self.num_epochs):
16            y_hat = [self.sigmoid(w@X[i]) for i in range(n)]
17            error = -(np.sum([y[i]*np.log(y_hat[i]) + (1-y[i])*np.log(1-y_hat
18            [i]) for i in range(n)]))
19            dw = X.T@(y-y_hat)
20            self.w = self.w - self.learning_rate*dw
21            return y_hat, error, self.w
22
23    def predict(self, X, w):
24        y_pred = self.sigmoid(X@w)
25        y_class = [1 if i > 0.5 else 0 for i in y_pred]
26        return y_class
27
28    def accuracy(self, y_true, y_pred):

```

```
return np.mean([1 if (y_true[i]==y_pred[i]) else 0 for i in range(
len(y_pred))])
```

Listing 1: Logistic Regression Code

Questions

1. Parameters of Logistic regression model are estimated using maximum likelihood estimation(MLE). State true or false.
2. Logit function gives _____of output variable.
3. Does the probability sum equal to 1 for sigmoid function in Logistic regression?
 - A. Yes, always.
 - B. Not always.
4. What can be done to avoid over-fitting in the model?
5. Which metric should be used to compare the logistic regression model output to the target variable?
 - A. AUC-ROC curve
 - B. Logloss
 - C. MSE