

ML:hw6

sblanco2465

April 2024

1 Logistic Regression

1. we just apply the rules of calculus (chain rule) to get the following answer.
Each step line indicates a step in calculation.

$$\begin{aligned} & \log(1 + \exp(-y_i w^T x_i)) \\ & \frac{1}{1 + \exp(-y_i w^T x_i)} * \frac{d}{dw} (1 + \exp(-y_i w^T x_i)) \\ & \frac{1}{1 + \exp(-y_i w^T x_i)} * \exp(-y_i w^T x_i) * -y_i x_i \\ & \frac{\exp(-y_i w^T x_i)}{1 + \exp(-y_i w^T x_i)} * -y_i x_i \end{aligned}$$

2. The objective function would be to find the weight vector that minimizes the loss function. we are given the loss function with a set of examples. In the given loss function we add up the loss for each example. Since this question asks for the loss of a single example we can get rid of the summation.
$$\arg \min_w [\log(1 + \exp(-y_i w^T x_i)) + \frac{1}{\sigma^2} w^T w]$$

3. we start with the derivative that we calculated in question 1

$$\frac{\exp(-y_i w^T x_i)}{1 + \exp(-y_i w^T x_i)} * -y_i x_i$$

we then calculate the derivative of $\frac{1}{\sigma^2} w^T w$

$w^T w$ is simply the sum of each of its terms squared which means its derivative is $2w$. Multiplying by our constant we get $\frac{2}{\sigma^2} w$

for a final answer of:

$$\frac{\exp(-y_i w^T x_i)}{1 + \exp(-y_i w^T x_i)} * -y_i x_i + \frac{2}{\sigma^2} w$$

$$w = w - \text{learningRate} * \left(\frac{\exp(-y_i w^T x_i)}{1 + \exp(-y_i w^T x_i)} * -y_i x_i + \frac{2}{\sigma^2} w \right)$$

4. given a set of examples (x_i, y_i)

w= random initial vector

for i in T: # T is total number of rounds, i is current round

pick a random example out of the set of examples (x_i, y_i)

gradient = (exp(-y_i w^T x_i) / (1 + exp(-y_i w^T x_i))) * -y_i x_i + (2 / sigma^2) w

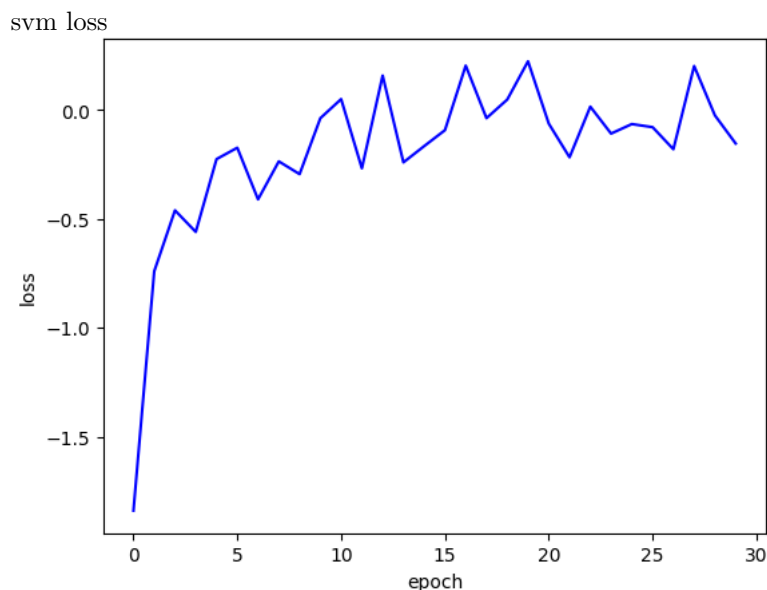
this is the gradient calculated in step 3

w = w - gradient * learning_rate

2 Experiments

2.1 SVM

- design decisions: I chose to implement svm in python using the pandas library. I utilized dataframes and numpy for data processing and representation.
- data representation: I chose to represent the data as `numpy.array((x0, y0), (x1, y1) ... (xn, yn))`. I did this so that I could make my algorithm in code look like the one in the slides.
- I also chose 30 epochs. This decision was made based on the f1 score not going up much beyond 30 epoch and even going down around 60 epoch.



2.2 Logistic regression

- design decisions: I did everything that I did with SVM above. This includes decaying the learning rate. I found that this improved performance.
- data representation: I use the same code for data representation for Logistic regression as I did for SVM.
- epoch: I chose 30 epoch on logistic regression for a similar reason as I did for SVM

logistic loss

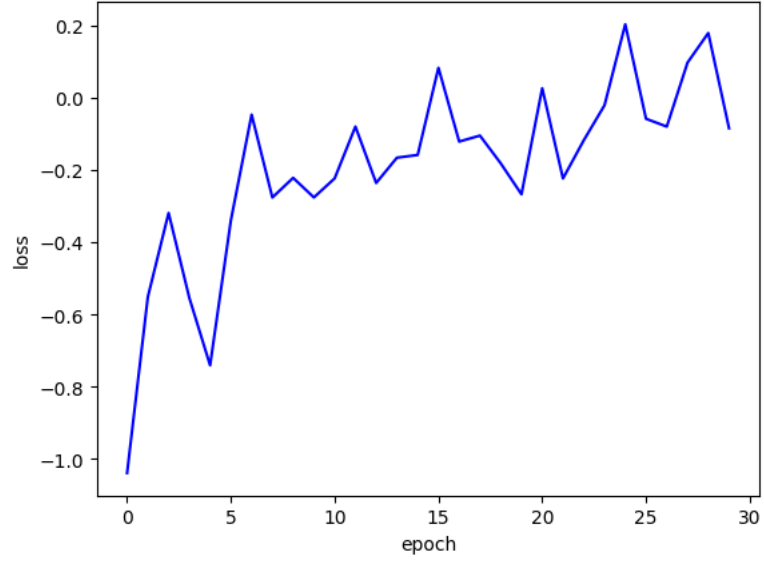


Table 1: Results Table

	Best hyper-parameters	avg Cross-validation P/R/F1	Test P/R/F1
SVM	C=10 $\gamma = .1$	F1=0.31 P=0.65 R=0.24	F1=0.44 P=0.39 R=0.53
Logistic Regression	C=1000 $\gamma = .01$	F1=0.4 P=0.69 R=0.29	F1=0.39 P=0.73 R=0.27