CSE 417T: Homework 3

Due: March 25 (Wednesday), 2020

Notes:

- Please submit your homework via Gradescope and check the submission instructions.

- Make sure you specify the pages for each problem correctly. You will not get points for problems that are not correctly connected to the corresponding pages.

- Homework is due by 11:59 PM on the due date. Remember that you may not use more than 2 late days on any one homework, and you only have a budget of 5 in total.

- Please keep in mind the collaboration policy as specified in the course syllabus. If you discuss questions with others you must write their names on your submission, and if you use any outside resources you must reference them. Do not look at each others’ writeups, including code.

- There are 5 problems on 2 pages in this homework.

Problems:

1. (30 points) The weight decay regularizer is also called $L_2$ regularizer, since $\bar{w}^T\bar{w}$ is the square of the 2-norm of the weight vector $\|\bar{w}\|_2 = \sqrt{\sum_{i=0}^{d} w_i^2}$. Another common regularizer is called $L_1$ regularizer, since 1-norm ($\|\bar{w}\|_1 = \sum_{i=0}^{d} |w_i|$) is used as the regularizer.

Below are the definitions of the two regularizations:

- $L_1$ regularization: $E_{\text{aug}}(\bar{w}) = E_{\text{in}}(\bar{w}) + \lambda \|\bar{x}\|_1$
- $L_2$ regularization: $E_{\text{aug}}(\bar{w}) = E_{\text{in}}(\bar{w}) + \lambda \bar{w}^T\bar{w}$

(a) Answer LFD Problem 4.8.

(b) Similar to Problem 4.8, we now aim to derive the update rule of gradient descent for minimizing the augmented error with $L_1$ regularizer. Note that the gradient of 1-norm is not well-defined at 0. To address this issue, we can utilize the subgradient idea defined as follows:

$$\frac{\partial}{\partial w_i} \|\bar{w}\|_1 = \begin{cases} +1 & \text{if } w_i > 0 \\ \text{any value in } [-1, 1] & \text{if } w_i = 0 \\ -1 & \text{if } w_i < 0 \end{cases}$$

\[1\]

When applying these regularizations to linear regression, they are called Ridge Regression ($L_2$ regularizer) and Lasso Regression ($L_1$ regularizer) respectively.
To simplify the discussion, we let $\frac{\partial}{\partial w_i} \|\vec{w}\|_1 = 0$ when $w_i = 0$. Please write down the update rule of gradient descent for $L_1$ regularization. (You can define a `sign()` function that returns $+1, 0, -1$ when the input is positive, zero, negative, respectively).

Note that, in practical implementation for $L_1$ regularizer, we can use truncated gradient \[\textbf{[1]}\]: At each step $t$, we first perform the update as what you derive above. Then for each $i$, if $w_i(t + 1)$ and $w_i(t)$ have different signs, we set $w_i(t + 1)$ to 0 (i.e., truncate the update in this case).

(c) Update your implementation of logistic regression in HW2 to include the $L_1$ and $L_2$ regularizers (use truncated gradient for $L_1$ regularizer). Examine different regularization strengths $\lambda = 0.001, 0.01, 0.05, 0.1$ (please feel free to try more choices of $\lambda$). Train your models on clevelandtrain.csv. For each trained model, report (1) the classification error on clevelandtest.csv and (2) the number of 0s in your learned weight vector. Describe your observations on the property of the $L_1$ regularizer.

For the other training parameters, please use the following. Normalize input data. Set learning rate $\eta = 0.01$. The maximum number of iterations is $10^6$. Terminate learning if the magnitude of every element of the gradient is less than $10^{-6}$. In calculating classification error, classify the data using a cutoff probability of 0.5.

You do not need to submit your code for this question.

2. (10 points) LFD Exercise (not Problem) 4.5
3. (25 points) LFD Problem 4.25 (a) to (c)
4. (15 points) LFD Problem 5.4. Note that the problem makes a simplifying definition: a stock is called “profitable” if it went up half of the days, and whether the stock goes up or down is a random draw from an unknown distribution that associates with how good the stock is. While this is not accurate in practice, please use this as the definition for your discussion.
5. (20 points) You have been hired by a biologist to learn a decision tree to determine whether a mushroom is poisonous. You have been given the following data:

<table>
<thead>
<tr>
<th>Color</th>
<th>Stripes</th>
<th>Texture</th>
<th>Poisonous?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Purple</td>
<td>No</td>
<td>Smooth</td>
<td>No</td>
</tr>
<tr>
<td>Purple</td>
<td>No</td>
<td>Rough</td>
<td>No</td>
</tr>
<tr>
<td>Red</td>
<td>Yes</td>
<td>Smooth</td>
<td>No</td>
</tr>
<tr>
<td>Purple</td>
<td>Yes</td>
<td>Rough</td>
<td>Yes</td>
</tr>
<tr>
<td>Purple</td>
<td>Yes</td>
<td>Smooth</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Use ID3 to learn a decision tree from the data (this is a written exercise – no need to code it up):

(a) What is the root attribute of the tree? Show the computations.
(b) Draw the decision tree obtained using ID3.

References