### HW Assignment 5, Theory

Problems marked with a (\*) are mandatory for ITCS 8156 students. Bonus problems are optional, solving them will result in extra points.

### 1 Gradient of Logistic Regression (20 points)

Prove that the gradient (with respect to  $\mathbf{w}$ ) of the negative log-likelihood error function for binary logistic regression corresponds to the formula shown in the lecture:

$$\nabla_{\mathbf{w}} E(\mathbf{w}) = \sum_{n=1}^{N} (h_n - t_n) \mathbf{x}_n \tag{1}$$

## 2 Binary Softmax Regression (20 points)

Show that Logistic Regression is a special case of Softmax Regression. That is to say, if  $\mathbf{w_1}$  and  $\mathbf{w_2}$  are the parameter vectors of a Softmax Regression model for the case of two classes, then there exists a parameter vector  $\mathbf{w}$  for Logistic Regression that results in the same classification as the Softmax Regression model, for any example  $\mathbf{x}$ .

## 3 Logistic Regression in sklearn (\*) (20 points)

In some ML packages, the objective function for binary logistic regression is formulated to appear similar with the SVM setting, where the labels  $t_n \in \{-1, +1\}$  (instead of  $\{0, +1\}$ ), and where a hyper-parameter C expresses the trade-off between model complexity and training error:

$$E(\mathbf{w}) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + C * \sum_{n=1}^{N} \ln(e^{-t_n(\mathbf{w}^T\mathbf{x}_n)} + 1)$$
(2)

- Show that the sum in the second term is equal with the negative log-likelihood.
- Compute the C parameter such that minimizing this objective is equivalent (has the same solution) as minimizing the standard objective shown on the slides in which the regularization parameter  $\alpha$  or  $\lambda$  is multiplied with the L2 norm term.

### 4 Gradient of Softmax Regression (20 bonus points)

Prove that the gradient (with respect to  $\mathbf{w}_k$ ) of the negative log-likelihood error function for regularized softmax regression corresponds to the formula shown in the lecture, for each class  $k \in [1..K]$ :

$$\nabla_{\mathbf{w}_k} E(\mathbf{w}) = -\frac{1}{N} \sum_{n=1}^N (\delta_k(t_n) - p(C_k | \mathbf{x}_n)) \mathbf{x}_n + \alpha \mathbf{w}_k$$
(3)

# 5 Submission

Submit your responses on Canvas as one file named theory.pdf. It is recommended to use an editor such as Latex or Word or Jupyter-Notebook that allows editing and proper formatting of equations. Alternatively, if you choose to write your solutions on paper, submit an electronic scan / photo of it on Canvas. Make sure that your writing is legible and the scan has good quality.