Exercise for MA-INF 2213 Computer vision SS18
13.04.2018
Submission on 19.04.2018

1 Regression

We consider the problem of object pose regression. The world variables $\mathbf{w} = [w_0\, w_1]$ given by rotating an object along two coordinate axes. Also given are observed 510 dimensional $\mathbf{x} = [x_0\, x_1\, \ldots\, x_{509}]$ PHoG[1] features per image.

Appropriate *regression_*.txt* files are provided for training regressing parameters and evaluating them. The header is arranged as [`numImages rowLength worldDimension`] and each row further on holds the concatenation $[\mathbf{w}_i\ \mathbf{x}_i]_{1\times 512}$ for image I_i.

Maximum Likelihood rule will be used for learning. As a performance metric, maximum likelihood estimate is used to compute the average squared error w.r.t ground truth value.

1. **Linear Regression:** Learn a linear regressor using the training data for both world variables independently and evaluate its performance on the test data. *(3 Points)*

2. **Non Linear Regression:** Learn a non-linear regressor for both variables independently using RBF kernels (parameter λ =1e-3). The centers for RBF kernels will be learnt by reducing the observed features into a 300 word codebook. Also evaluate its performance on the test data. *(4 Points)*

3. **Dual Model Regression:** Learn a dual-model regressor for both variables independently using RBF function (parameter λ =1e-3) as the kernel. Also evaluate its performance on the test data. *(3 Points)*

2 Classification

We consider the problem of binary classification (bottles and horses). Given are the 510 dimensional PHoG features for each class, separated for training and testing. The data is arranged in a similar manner as above.

1. **Logistic Regression:** Using the *bottles* as positive and *horses* as negative examples, learn a linear classifier based on logistic regression. You may choose a simple gradient descent or the Newton's method for optimization.
   Given maximum iterations of 1e4, comment on the effect of step size on the convergence of optimization by observing the evolution of the cost. Finally, benchmark the performance of the classifier using the test data at $Pr(\mathbf{w}_i|\mathbf{x}_i, \Psi) = 0.5$ by evaluating accuracy

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

where TP and FN stand for true positive and false negative respectively. *(6 Points)*

2. **Derivatives of loss function:** Given the loss function for logistic linear regression parameterized by ϕ (Eq. 9.6 in [2])

$$L = \sum_{i=1}^{I} w_i \log\left[\frac{1}{1 + \exp\left[-\phi^T \mathbf{x}_i\right]}\right] + \sum_{i=1}^{I} (1 - w_i) \log\left[\frac{\exp\left[-\phi^T \mathbf{x}_i\right]}{1 + \exp\left[-\phi^T \mathbf{x}_i\right]}\right]$$

Show the gradient to be

$$\frac{\partial L}{\partial \phi} = -\sum_{i=1}^{I} \left(\frac{1}{1 + \exp\left[-\phi^T \mathbf{x}_i\right]} - w_i\right) \mathbf{x}_i \tag{2}$$

(4 Points)

References

[1] A. Bosch, A. Zisserman, and X. Munoz, Representing shape with a spatial pyramid kernel, In Proceedings of the International Conference on Image and Video Retrieval, pp. 401-408, 2007

[2] C. Bishop, Pattern Recognition and Machine Learning, Springer 2006