

## Problem Set — Machine Learning

### Problem 1 (Data Set Preparation (10 points))

Download sample machine learning datasets from the UCI Irvine Repository at <http://archive.ics.uci.edu/ml/>.

1. Obtain 5 datasets for binary classification (hint: use real-valued datasets).
2. Import them into MATLAB, Python with NumPy, R, or any other numerical analysis platform of your choice.
3. Create 2 copies of each dataset
  - Original dataset
  - Rescale data to 0 mean and unit variance coordinate-wise

Provide the (pseudo)-code for these routines.

### Problem 2 (Perceptron (20 points))

1. Implement the basic Perceptron algorithm for binary classification.
2. Split each dataset (all 3 copies) 80 / 20 into a training and a testing dataset.
3. Compute the average classification error on training and test set after running the Perceptron once on the training set, and after 10 passes over the training set.
4. Incorporate a decreasing learning rate  $\eta_t = \frac{c}{\sqrt{t+t_0}}$  (e.g.  $c = 0.1$  and  $t_0 = 1000$ ) and repeat the experiments.

Provide the (pseudo)-code and errors for these routines. What happens if you change  $c$  and  $t_0$ ?

### Problem 3 (Rotation Invariance (10 points))

Prove that the stochastic gradient descent algorithms are invariant under rotation. That is, show that if we replace  $x$  by a rotated copy,  $Ux$  where  $U^T U = \mathbf{1}$ , then the classification / regression results of the algorithm remain unchanged.

### Problem 4 (Game Show (10 points))

Assume that in a TV show the candidate is given the choice between three doors. Behind two of the doors there is a pencil and behind one there is the grand prize, a car. The candidate chooses one door. After that, the showmaster opens another door behind which there is a pencil. Should the candidate switch doors after that? What is the probability of winning the car?

### Problem 5 (Robustness — bonus (10 points))

Show that for the problem of quadratic regression, that is, find a function  $f(x) = \langle x, w \rangle$  such that the loss  $\sum_i (y_i - f(x_i))^2$  is minimized, a single choice of  $y_i$  suffices to change the  $f$  by an arbitrary amount.

Show that if we replace the loss by  $\sum_i |y_i - f(x_i)|$  the change in  $f$  is bounded if we change  $y_i$  arbitrarily. Hint: use the first-order optimality conditions of the optimization problem.