

# Week 6 Exercise Sheet

The following exercises have different levels of difficulty indicated by (\*), (\*\*), (\*\*\*). An exercise with (\*) is a simple exercise requiring less time or effort to solve compared to an exercise with (\*\*\*), which is a more complex exercise.

## 1 Logistic Regression

1. (\*\*) Derive  $\pi$  from  $\log(\frac{\pi}{1-\pi}) = \mathbf{w}^T \mathbf{x}$ , i.e. derive the logistic sigmoid function from the logit function.
2. (\*) In a binary (two-class) logistic regression model, the weight vector  $\mathbf{w} = [4, -2, 5, -3, 11, 9]$ . We apply it to some object that we'd like to classify; the vectorised feature representation of this object is  $\mathbf{x} = [6, 8, 2, 7, -3, 5]$ . What is the probability, according to the model, that this instance belongs to the positive class (i.e  $y=1$ )?
3. (\*\*\*) Consider flipping a coin 20 times and recording each result  $y_i = \{0, 1\}$ . Using the log likelihood  $l(\pi; \mathbf{y})$  derive the maximum likelihood estimation (MLE) for  $\pi$  by finding the derivative w.r.t  $\pi$  and setting this equal to zero ( $\partial l(\pi; \mathbf{y}) / \partial \pi = 0$ ). Is the result what you would have expected?

## 2 Automatic differentiation

Let  $\mathbf{f}$  be a vector-valued function that maps from  $\mathbb{R}^3$  to  $\mathbb{R}^2$

$$y_1 = f_1(x_1, x_2, x_3) = x_1 x_3 + \log(x_2 + x_1) \times \exp(-x_3), \quad (1)$$

$$y_2 = f_2(x_1, x_2, x_3) = \exp(-x_2) + \cos(x_1 x_3). \quad (2)$$

1. (\*) Compute the Jacobian using manual differentiation and evaluate the Jacobian at the point  $(x_1 = 3, x_2 = 5, x_3 = 1)$
2. (\*) Compute the Jacobian at the same point that in the previous point, but using finite difference approximation.
3. (\*) Draw the computational graph.

4. (\*\*) Compute the Jacobian using AD in forward mode. Write the expressions for all the intermediate variables  $\dot{v}_i$  in the forward tangent trace.
5. (\*\*) Compute the Jacobian using AD in reverse mode. Write the expressions for all the adjoints  $\bar{v}_i$  in the reverse derivative trace.