Introduction to ML (CS771), 2024-2025-Sem-I		Total Marks	60
Midsem exam. September 15, 2024		Duration	2 hours
Name		Roll No.	

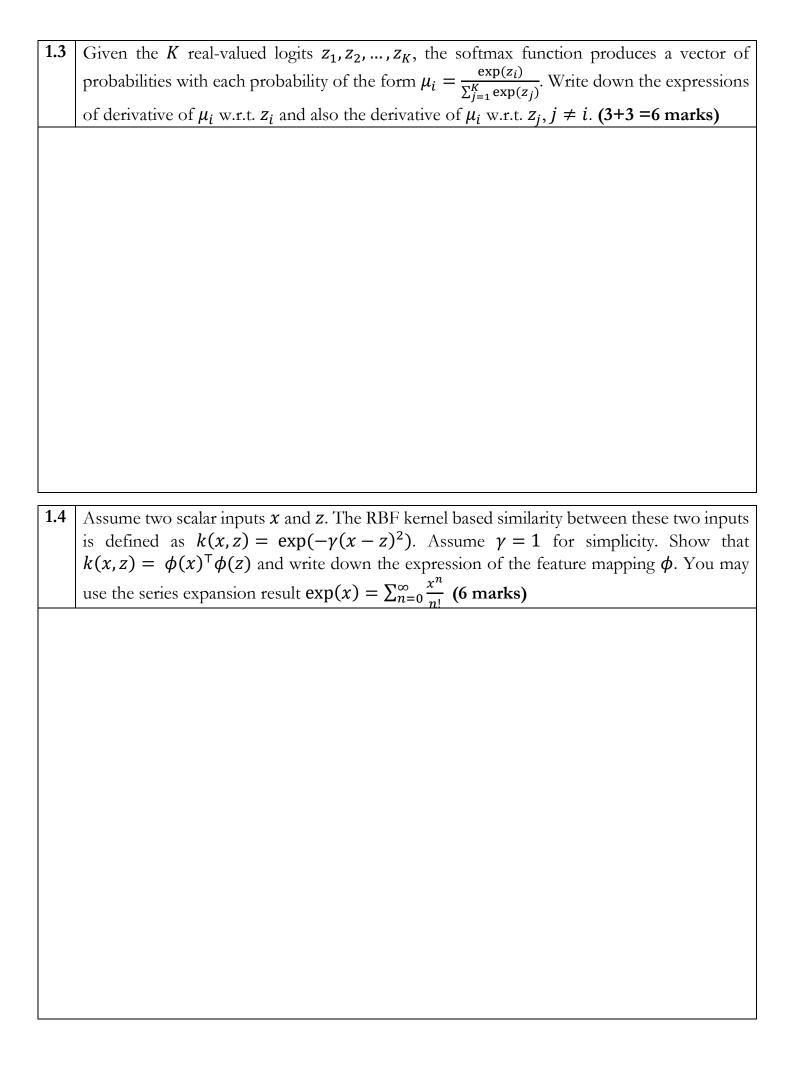
Instructions:

- 1. Clearly write your name (in block letters) and roll number in the provided boxes above.
- 2. Write your final answers concisely in the provided space. You may use blue/black pen.
- **3.** We may not be able to provide clarifications during the exam. If any aspect of some question appears ambiguous/unclear to you, please state your assumption(s) and answer accordingly.
- 4. The last page (page 6) of this booklet can be used for rough work.

Section 1 (Short Answer Questions): Answer the following questions concisely in the space provided below the question.

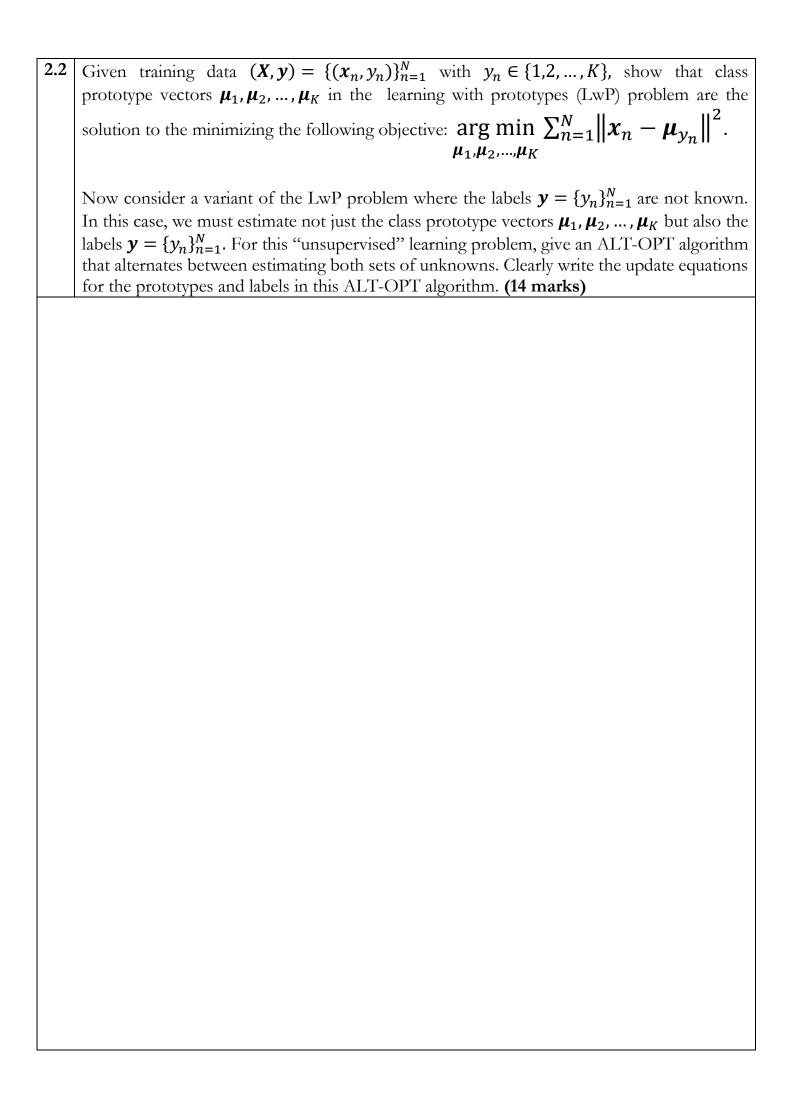
1.1	Assume a scalar-valued function $f(\mathbf{w})$, with $\mathbf{w} = [w_1, w_2, w_3, w_4]^{T} \in \mathbb{R}^4$, defined as
	$f(\mathbf{w}) = (w_1 - w_2)^2 + (w_2 - w_3)^2 + (w_3 - w_4)^2 + (w_4 - w_1)^2$. Write down the final
	expression (don't show the steps) of gradient of $f(\mathbf{w})$ w.r.t. \mathbf{w} . Without using the gradient, can you answer what is the minima of this function? If so, answer what it is. If not, state why
	you can't. Also, is $f(w)$ convex? Briefly justify the answer. (2+2+2 =6 marks)
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1.4	which of these are examples of convex sets: (1) the set of D -dimensional vectors with all
	non-negative entries, (2) set of D-dimensional vectors that have at most $K < D$ nonzero
	entries. Briefly justify your answers. (2+2 =4 marks)



-	1.5	Suppose we want to train a Perceptron algorithm for binary classification but in a manner that the hyperplane has a margin, and not just equal margin γ on both sides but uneven
		margins (γ_+ towards the positive side and γ on the negative side; assume $\gamma_+ > \gamma$). Briefly
		describe using the necessary equation(s) how you would accomplish this. In what cases,
_		having an uneven margin may be desirable? (6 marks)
-	1.6	Write down the expression for the gradient descent (GD) update for the ridge regression
-	1.6	model which is the same as least squares (LS) linear regression with an additional ℓ_2 -squared
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Section 2 (Long Answer Questions): Answer the following questions concisely in the space provided below the question.		
2.1	The binary cross-entropy loss used in logistic regression with weight vector $\mathbf{w} \in \mathbb{R}^D$ is given by $L(\mathbf{w}) = \sum_{n=1}^N -[y_n \log \sigma(\mathbf{w}^{T} \mathbf{x}_n) + (1-y_n) \log (1-\sigma(\mathbf{w}^{T} \mathbf{x}_n))]$, where $\sigma(.)$ denotes the sigmoid function. Derive the Newton's method updates for \mathbf{w} for optimizing this loss. Note: If you find it more convenient with matrix-vector notation then note that the above loss can also be written as $L(\mathbf{w}) = -\mathbf{y}^{T} \log \sigma(\mathbf{X}\mathbf{w}) - (1-\mathbf{y})^{T} \log (1-\sigma(\mathbf{X}\mathbf{w}))$ where \mathbf{X} denotes the $\mathbf{N} \times \mathbf{D}$ feature matrix and \mathbf{y} is the $\mathbf{N} \times 1$ label vector, and log and sigmoid functions are applied element-wise on their vector arguments (12 marks)	



Only for Rough Work