

## Assignment: Understanding Loss Functions in Supervised Learning

**Due Date:** [Insert Due Date Here]

### Introduction:

In supervised learning, the choice of a loss function is a critical step that dictates how our model learns and what objective it optimizes. Building upon our understanding of supervised learning as (1) choosing a representation, (2) choosing a loss function, and (3) minimizing the loss, this assignment will delve deeper into the concept and application of various loss functions, particularly in the context of classification.

**Instructions:** Please answer the following questions thoroughly, referencing the provided lecture notes where appropriate.

### Part 1: Fundamental Concepts of Loss Functions

#### Defining Loss Functions:

What is the primary purpose of a loss function in supervised learning?

How does a loss function relate to the overall goal of minimizing empirical risk?

#### Loss Functions Across Problem Types:

The notes discuss different types of supervised learning problems. For each of the following, identify the typical target space ( $Y$ ) and provide the formula for a commonly used loss function mentioned in the text:

Linear Regression

Binary Classification (using  $y \in \{-1, 1\}$ )

Multiclass Classification

### Part 2: Margin-Based Loss Functions for Binary Classification

#### The Concept of Margin:

In binary classification (with labels  $y \in \{-1, 1\}$ ), what is the "margin" for an example  $(x, y)$  with respect to a parameter vector  $\theta$ ? Provide its mathematical expression.

Explain why a large positive margin is desirable for a correctly classified example.

### **Desired Characteristics of Classification Loss:**

Describe the general shape and behavior (as depicted in Figure 1 of the notes) that we desire for a classification loss function  $\phi(z)$  with respect to the margin  $z$ . Specifically, how should  $\phi(z)$  behave as  $z \rightarrow \infty$  and as  $z \rightarrow -\infty$ ?

### **The Zero-One Loss:**

Provide the formula for the zero-one loss,  $\phi_{zo}(z)$ .

From an intuitive perspective, why might the zero-one loss seem like the "most natural" choice for classification?

Despite its intuitive appeal, the notes state that  $\phi_{zo}$  is "discontinuous, non-convex, and NP-hard to minimize." Briefly explain why these characteristics make it problematic for practical optimization in machine learning.

## **Part 3: Common Classification Loss Functions**

### **Comparing Practical Loss Functions:**

The notes introduce three commonly used margin-based loss functions that overcome the limitations of the zero-one loss. For each of the following, provide its mathematical formula and briefly describe its key characteristics or behavior with respect to the margin ( $z = yx^T\theta$ ), referencing Figure 2:

**(i) Logistic Loss ( $\phi_{\text{logistic}}(z)$ )**

**(ii) Hinge Loss ( $\phi_{\text{hinge}}(z)$ )**

**(iii) Exponential Loss ( $\phi_{\text{exp}}(z)$ )**

### **Loss Functions and Algorithms:**

The choice of a loss function often gives rise to specific machine learning algorithms. Which well-known machine learning algorithms are associated with:

The hinge loss ( $\phi_{\text{hinge}}$ )?

The exponential loss ( $\phi_{\text{exp}}$ )?

### **Part 4: Empirical Risk Minimization**

#### **Empirical Risk for Margin-Based Losses:**

Given a training set of pairs  $\{(x(i), y(i))\}_{i=1}^m$  and a margin-based loss function  $\phi(z)$ , write down the general formula for the empirical risk  $J(\theta)$  that we aim to minimize.

Explain how minimizing this empirical risk helps us find an optimal parameter vector  $\theta$  for our model.