CS 203: Software Tools & Techniques for Al IIT Gandhinagar Sem-II - 2024-25

LAB 06

Lead TA: Section 1- Eshwar Dhande; Section 2- Himanshu Beniwal

Total marks: 100

Submission deadline: Tuesday, 25/02/2025 11:59 PM

Submission guidelines:

- 1. Code should be added to a GitHub repository, and the **repository details** should be shared in the pdf.
- 2. **Submit the PDF showing screenshots** of all steps involved in the following code.

Note: By submitting this assignment solution you confirm to follow the IITGN's honor code. We shall strictly penalize the submissions containing plagiarized text/code.

Objective:

The goal of this assignment is to learn about experiment tracking, version control, and reproducibility in machine learning workflows. You will set up experiment tracking using **Weights** and **Biases**.

Section 1: MLP Model Implementation & Experiment Tracking

- 1. Implement a Multi-Layer Perceptron (MLP) Using the Iris Dataset (05%)
 - Load the Iris dataset using sklearn.datasets.load_iris.
 - Extract features and labels, ensuring labels are one-hot encoded.
 - Split the dataset into:

Training set: 70%Validation set: 10%Testing set: 20%.

• Normalize feature values to [0,1] using standard scaling.

2. Define and Train the MLP Model (05%)

- Construct a **Multi-Layer Perceptron (MLP) model** with the following architecture:
 - o **Input layer**: 4 neurons (for 4 features).
 - Hidden layer: 16 neurons, ReLU activation.
 - Output layer: 3 neurons (for each class), softmax activation.
- Train using:
 - Loss function: Categorical cross-entropy.
 - o Optimizer: Adam.
 - Learning rate: 0.001.
 - o Batch size: 32.
 - o Epochs: 50.
- Track and store both training and validation loss during training.

3. Evaluate Model Performance (10%)

- Compute and store the following metrics using the **test set**:
 - Accuracy
 - Precision
 - Recall
 - o F1-score
 - Confusion matrix (visualized using Matplotlib).
- Plot training and validation loss curves over epochs using Matplotlib.

4. Set Up Experiment Tracking with Weights & Biases (W&B) (30 %)

- Log the following details:
 - Model architecture: Number of layers, neurons, activation functions.
 - **Hyperparameters**: Learning rate, batch size, number of epochs.
 - o Training and validation loss per epoch.
 - Final evaluation metrics.
 - Confusion matrix and loss curve visualizations.

5. Submission Requirements

- Submit:
 - Python code for training, testing, and evaluation.
 - Screenshots of the W&B dashboard displaying:
 - Model architecture.
 - Hyperparameters.
 - Logged metrics.
 - Final evaluation results.
 - Confusion matrix visualization.
 - Training and validation loss curves.

Section 2: Hyperparameters

This section aims to perform a hyperparameter search to improve the performance of a **custom model** that distinguishes between any two classes (positive/negative or anything).

Task 1: Hyperparameter Optimization (20%)

- Use the model trained in the previous section.
- Train the model on the batch size of [2 & 4], learning rate [1e-3 and 1e-5], and epochs [1, 3, and 5].
- Train the model and measure the accuracy and F1 over the test set. Plot the confusion matrix over the test-set predictions.
 - Plot using the truth labels and predicted labels in matplotlib.
- Show the inputs, prediction, and truth values for five samples from the test set.

Task 2: Automated Hyperparameter Search (20%)

- Use the Grid Search over the parameters defined above, <u>Random Search</u>, and <u>Hyperband + Bayesian Optimization hyperparameter</u> to search for the hyperparameters defined in Task 1.
- Create a table (Each row with a configuration and column with Accuracy and F1) for Grid, Random, Hyperband, and Bayesian search and compare their accuracy and F1.

Evaluation Criteria

Perform hyperparameter optimization using AutoGluon

- Plot the scatter plot for training vs validation loss.
- A relation (direct or inverse) between the hyperparameters and their impact on the performance (Hypothetically, epoch is directly proportional to performance, but batch size is inversely proportional).
- Describe the performance for each hyperparameter combination over accuracy and F1.

Compare manual tuning vs. automated search

Which approach is better and why? (At most five lines of explanation)

• Plots for the training vs validation loss for each hyperparameter configuration.

Documentation (10%)

• Proper documentation of code, graphs, and metrics.