Effective Teaching of “Machine Learning”

(A Module in the CSEDU – Certificate Program in CS Education)

Objective:

The aim of this module is to help teachers in colleges/universities (attendees) improve their teaching of the Machine Learning course, as per its prescribed AICTE syllabus (given at the end of this document). On attending this module, the attendees will improve their teaching of this course leading to improved learning by their students, and thereby more students achieving the learning outcomes of the AICTE course. This module is part of the Certificate Program in CS Education initiative (csedu.iiitd.ac.in).

The main learning outcomes of *this module* are (at the end of the module, an attendee will):

- Have clearer understanding of importance of this course in a CSE program, desired learning outcomes established in the AICTE course, and course syllabus
- For each topic in the AICTE syllabus, have a deeper understanding of concepts, what is important, how to teach, what type of assignments to give, etc.
- Appreciate how some (contemporary) teaching tools and techniques could be brought to the classrooms while teaching Machine Learning

The module will focus on delivering the Essential Learning Outcomes of the AICTE course syllabus. Some advanced topics may also be discussed, based on inputs from attendees towards the end of this module.

Requirements for Module Attendees

The attendees for this module should:

- Have taught machine learning in the past or planning to take up in near future
- Have sufficient background knowledge in topics covered in the AICTE ML course
- Have access to a good laptop (or desktop) and internet
- Commit to spending at least 5 hrs per week (avg) for the module
- Have familiarity with Python

Module Syllabus

Each weekly session will discuss one of the key topics in the AICTE syllabus, and an appropriate teaching methodology that suits this topic.

The week-wise syllabus for this module is given in the table. It may be revised based on how the module progresses and feedback of attendees:

Wk	M	Topic or Module from AICTE syllabus to be discussed.	Approach	Self-work for the week (illustrative)
1	M1	• Introduction to this module • What is Machine Learning and how is it related to other areas of computer science? • How is ML related to other related terms like AI, DL, DS, etc? • Brief introduction to practical and pedagogical challenges in teaching • Our course plan and teaching/styles	Lecture	Quick recap of python and Jyupiter notebook
2	M1	• A quick tour of ML curriculum/course and different ways of sequencing/organizing • Recap of Key concepts in ML • Success stories/Case Studies (industry use case) and expose the ML pipeline • Data, Representation and Visualization • Appreciate data and visualize using python notebooks provided.	Primarily Lecture May be show some small video clips (industrial use case) (how to use external videos for strengthening the teaching) Show python notebook (preview)	Recap of basic ML concepts (play videos) and Q&A. Make everyone comfortable with the keyword space.
3	M1	• Machine Learning Problems and Formulations • Popular Paradigms of Machine Learning • Problem of Classification and Regression • Details: Linear regression and see how a ML topic could be planned • Use of Python notebooks in teaching and learning • Popular tools and resources for effective teaching.	How to use the modern Tools to make the teaching effective (Tutorial could introduce python notebooks and running)	Python notebooks Running Demo and showing Plotting Use of Cloud/for teaching Educational credits (factual) Contrast between classical vs using tools Panda, data handling (?) (students need to learn; teachers may not)

4	M2	- Dimensionality Reduction and PCA - How to teach PCA? - What will students find difficult? - How to prepare questions/homeworks?	How to demonstrate teaching with a full life cycle? (End2End Teaching) How to use Online Resource for planning a full lecture/topic? How to start preparing for a lecture (look at popular videos, blogs, courses online, figure out the full breadth of topics)? Which are the popular sources? How to structure the lesson? (short videos, mix of theory and hands-on, recall based Qs) How to create theory assignments (what are some good sources from which Qs can be curated)? How to create programming assignments (starter codes, datasets, variations)	One Lab experiment involving PCA

5	M2	● Decision Trees for Classification ● Problem of Overfitting ● Idea of Regularization	(full cycle) Setting home works,questions ,exams	One Lab experiment involving Decision Trees and Overfitting
6	M2	● Notion of Training, Validation, Testing, ● Generalization	(full cycle) Creating programming exercises (start from some library)	Demonstrate the role of Validation data and error estimate
7	M3	● K-Means Algorithm ● K-Means: Unsupervised Learning and associated optimization problems ● More into K-Means ● Formulating an ML optimization problem (in class exercise)	How to strengthen the analytical background of the student? Strengthening the analytical foundations of Students in ML Use of boards (also electronic) Peer and and Group Learning Simple to details and fundamental questions Why is theory important? Motivating students to appreciate theory, what are some tricks? Some motivating examples where practice will not be effective without	Technical writing (maybe briefly introduce LaTeX)

			knowing the theory. How to train students to read technical notation. Case study could be SVMs (which has a lot of notation, but also geometrical intuition)	
8	M3	● Conceptual introduction to SVM ● Formulation and objective functions ● Beauty and Elegance of SVMs connecting to theoretical claims and practical utility	Inverted Class	Lab exercise for linear SVM with - Visualize support vectors in toy 2D data - Use Kernels with not much explanation
9	M3	● Probabilistic view of ML, Recap of Basic Probability Terms ● Bayesian Perspective ● Logistic regression	Lecture	Use of Naive Bayes Classifier in a Lab
10	M4	● Introduction to Neuron Models, ● Multi Layer Perceptrons ● MLPs for Classification and Regression ● Loss functions and Regularization	Parallel or different views of a specific topic (decision boundary, feature composition, classifiers) Notebook/Programming/Code/Demo Centric Teaching	Run Simple MLP in Pytorch
11	M4	● Gradient Descent Optimization ● Backpropagation Algorithm ● Chain Rule and Derivation	Notebook/Programming/Code/Demo Centric Teaching	Show how BP works on a toy MLP.

			Also as inverted	
12	M4	• Intro. To Deep Learning • Introduction to CNN • Why CNNs and DL yield impressive results? • Practical issues in working with DL	Notebook/Programming/Code/Demo Centric Teaching	A CNN classifier and some visualization
13		Advances or Special Topic Specific	Participant request; Lecture	
14		Advances or Special Topic Specific	Participant request; Lecture	
15		Advances or Special Topic Specific	Participant request; Lecture	

Schedule

The module will meet online once a week. In addition, a weekly help session to clear doubts and to help with the assignment will be provided through TA s. Details about joining these sessions will be provided later.

- **Weekly Session**: Thursday, 4:30 pm to 6 pm (Friday 4:30 -6 pm if Thursday is holiday)
- **Weekly help Session**: Saturday, 4:00- 5:30 pm (or 4:30 pm to 6 pm)

Text to be used for the Module

The textbook suggested in the AICTE syllabus will be used as the basis of this module.

Resources to be provided to attendees.

- A curated online resource aligned with the AICTE course
- Lecture Notes / ppt for the different topics in the course
- Some sample assignments for each of the major module
- Slides/material which are used for teaching these modules.

Post Module Support

- A mailing list will be created for the discussions
- An online symposium (2 Hrs) every quarter with
  - A brief Talk
  - Panel/Discussion/Sharing Experiences
  - Q&A

To maintain the connections and learn from each other.

Course code: CSXXX	Machine Learning	3L:1T: 0P	Credits: 4	Pre-Reqs:

Learning Outcomes of the course (i.e. statements on students' understanding and skills at the end of the course the student shall have):

Essential (<=6):

1. Understanding popular ML algorithms with their associated mathematical foundations
1. Capability to implement basic algorithms using basic (python) libraries. Have hands-on experience in applying ML to problems encountered in various domains
2. Make aware of the role of data in the future of computing and solving real-world problems.
3. Helping them connect/map real-world problems to the appropriate ML algorithm(s) to solve them
4. Have a solid mathematical understanding of the popular ML algorithms
5. Have exposure to high level ML libraries or frameworks such as TF, pytorch
6. Have awareness about the importance of core CS principles such as algorithmic thinking and systems design in ML

Desirable/Advanced (<= 3):

- **Nil**

Detailed contents for Essential Learning Outcomes:

Module (appx dur in wks)	Topics	Pedagogy / teaching suggestions	Nature of lab / assignment / practice
Module 1: Introduction to ML (3-4 weeks)	(i) Motivation and role of machine Learning in computer science and problem solving, (ii) Representation (features), linear transformations, Appreciate linear transformations and matrix		

	vector operations in the context of data and representation. (iii) Problem formulations (classification and regression). (iv) Appreciate the probability distributions in the context of data, Prior probabilities and Bayes Rule. (v) Paradigms of Learning (Supervised, Unsupervised, and a brief overview of others)		
Module 2: Fundamentals of ML (3-4 weeks)	(i) PCA and Dimensionality Reduction (ii) Nearest Neighbours and KNN. (iii) Decision Tree Classifiers (iv) Generalization and overfitting (v) Notion of Training, Validation and Testing		
Module 3: Selected Algorithms	(i) Ensembling and RF (ii) Linear SVM, (iii) K Means, (iv) GMM, (v) EM, (vi) Naive Bayes		
Module 4: NN Learning	(i) Role of Loss Functions and Optimization, (ii)		

	Gradient Descent and Perceptron/Delta Learning, (iii) MLP, (iv) Backpropagation (v) MLP for Classification and Regression, (vi) Regularization, Early Stopping (vii) Introduction to Deep Learning		

Suggested text books / Online lectures or tutorials: To be added soon

Suggested reference books / Online resources: To be added soon