DS615: Neural Network and Deep Learning

Instructor:	Sourish Dasgupta
Prerequisites:	Python, Linear Algebra, Probability Theory, Calculus, Machine Learning
Slot:	M.Sc. DS Semester-II
Category:	Core
Course Credits(L--T--P--Cr):	3--0--2--4
Lectures:	Yes (Offline)
Lab and Practical:	Yes
TA contact info:	TBD

Course Description:

This course provides an in-depth exploration of neural networks and deep learning, emphasizing their applications in data science. Students will learn the theoretical foundations and practical implementations of various neural network architectures, enabling them to tackle complex data-driven challenges.

Course Objectives:

- Understand the fundamental concepts of neural networks and deep learning.
- Implement and train various neural network architectures using modern frameworks.
- Apply deep learning techniques to real-world data science problems, including image and text data.
- Evaluate and optimize model performance using appropriate metrics and techniques.
- Stay informed about current trends and advancements in deep learning resear**ch.**

Course Structure

- **Lecture:** Learn the foundational concepts of modern Deep Learning architectures and applications
- **Project:** The course will be project-driven, where a specific application-oriented problem will be defined and given. Every lecture will be designed in the context of solving the given problem with an introduction to necessary technologies. Bi-weekly assignments will be given, and assignments will be designed as necessary stepping stones toward the completion of the project.

Suggested Books:

- "Deep Learning" by Ian Goodfellow, Yoshua Bengio, and Aaron Courville.
- "Neural Networks and Deep Learning" by Michael Nielsen.

Course Outcomes:

By the end of this course, students will be able to:

- **Comprehensive Understanding of Neural Networks:** Grasp the fundamental principles and architectures of neural networks, including feedforward, convolutional, and recurrent networks.

DS615: Neural Network and Deep Learning

- **Proficiency in Deep Learning Frameworks:** Gain hands-on experience in implementing and training neural networks using modern deep learning libraries such as TensorFlow or PyTorch.

- **Application of Deep Learning to Data Science Problems:** Apply deep learning techniques to address real-world data science challenges, including tasks involving image and text data.

- **Model Evaluation and Optimization Skills:** Develop the ability to assess model performance using appropriate metrics and refine models through techniques like hyperparameter tuning and regularization.

- **Awareness of Ethical Considerations in AI:** Understand the ethical implications of deploying deep learning models, including issues related to bias, fairness, and societal impact.

- **Preparation for Advanced AI Endeavors:** Establish a solid foundation for pursuing further studies or careers in artificial intelligence, machine learning, and data science.

P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
X	X	X			X				X	X	X

Evaluation Scheme

- **Mid-semester Exam:** 20 %
- **End-semester Exam:** 30 %
- **Group Project-Assignments:** 50 % (group size will be a maximum of 4 students)

Grading Policy

For Credit:
AA: >=85%; AB: >=75%; BB: >=65%; BC: >=55%; CC: >=45%; CD: >=35%; DD: >=25%; F: <25%
For Audit:
Pass: >=25%

Course Plan:

Units	Topics	Number of Lectures
Introduction to Neural Networks and Deep Learning	• Overview of machine learning and the role of neural networks. • Biological inspiration and history of neural networks. • Key components: neurons, layers, activation functions.	3

DS615: Neural Network and Deep Learning

	• Introduction to deep learning and its significance in data science.	
Fundamentals of Neural Networks	• Mathematical foundations: linear combinations, activation functions. • Feedforward neural networks and the forward propagation process. • Loss functions and their role in training. • Introduction to backpropagation and gradient descent.	5
Training Neural Networks	• Gradient descent variants: stochastic, mini-batch, and batch. • Optimization algorithms: RMSprop, Adam. • Overfitting and underfitting: causes and solutions. • Regularization techniques: L1/L2 regularization, dropout.	6
Deep Neural Networks	• Understanding depth: shallow vs. deep networks. • Challenges in training deep networks: vanishing and exploding gradients. • Techniques to facilitate training: batch normalization, residual connections. • Introduction to popular deep learning frameworks (e.g., TensorFlow, PyTorch)..	4
Convolutional Neural Networks (CNNs)	• Motivation and applications in image processing. • Convolution operations and feature extraction. • Pooling layers and their role in dimensionality reduction. • Architectures: ResNet.	3

DS615: Neural Network and Deep Learning

Recurrent Neural Networks (RNNs)	● Sequence data and the need for RNNs. ● Architecture and functioning of RNNs. ● Challenges: vanishing gradients and long-term dependencies. ● Variants: Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs).	4
Unsupervised Learning and Generative Models	● Autoencoders: architecture and applications. ● Variational Autoencoders (VAEs). ● Generative Adversarial Networks (GANs): concept and training. ● Applications: data augmentation, anomaly detection.	4
Model Evaluation and Hyperparameter Tuning	● Evaluation metrics: accuracy, precision, recall, F1-score. ● Cross-validation techniques. ● Hyperparameter tuning methods: grid search, random search, Bayesian optimization. ● Model interpretability and explainability.	4
Advanced Topics and Current Trends	● Transfer learning and fine-tuning pre-trained models. ● Ethical considerations in deep learning. ● Recent advancements and research directions in deep learning	3

Lectures: 36 (tentative)