

# Artificial Intelligence & Machine Learning Course Syllabus

## Course Overview

This course introduces the foundational concepts of Artificial Intelligence (AI) and Machine Learning (ML). It covers theory, algorithms, and real-world applications, giving students the knowledge to understand and implement AI and ML solutions. Students will learn about supervised, unsupervised, and reinforcement learning, as well as AI frameworks and tools.

## Course Objectives

By the end of the course, students will:

- Understand key AI and ML concepts.
- Be familiar with supervised, unsupervised, and reinforcement learning.
- Gain hands-on experience with ML algorithms.
- Learn to evaluate model performance and tune hyperparameters.
- Understand ethical considerations in AI/ML.

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## Course Structure

### Week Topics

- 1 Introduction to Artificial Intelligence**
  - History of AI
  - Key AI concepts and applications
  - Differences between AI, Machine Learning, and Deep Learning
- 2 Introduction to Machine Learning**
  - Overview of ML types: Supervised, Unsupervised, and Reinforcement Learning
  - ML use cases and real-world applications
- 3 Linear Algebra & Probability for Machine Learning**
  - Vectors, Matrices, and Operations
  - Probability and Statistics concepts
  - Python for basic math operations
- 4 Supervised Learning: Regression**
  - Linear Regression
  - Polynomial Regression
  - Evaluation Metrics (RMSE,  $R^2$ )
- 5 Supervised Learning: Classification**
  - Logistic Regression
  - Support Vector Machines (SVMs)

## Week Topics

- k-Nearest Neighbors (k-NN)
- Performance Metrics (Accuracy, Precision, Recall, F1-Score)

### **Model Evaluation & Hyperparameter Tuning**

- 6
- Cross-Validation
  - Grid Search, Random Search
  - Bias-Variance Tradeoff

### **Unsupervised Learning: Clustering**

- 7
- k-Means Clustering
  - Hierarchical Clustering
  - Gaussian Mixture Models (GMMs)

### **Unsupervised Learning: Dimensionality Reduction**

- 8
- Principal Component Analysis (PCA)
  - t-SNE, UMAP
  - Applications in Visualization

### **Introduction to Neural Networks**

- 9
- Perceptron and Multi-layer Perceptron (MLP)
  - Activation Functions (ReLU, Sigmoid, etc.)
  - Backpropagation

### **Deep Learning & Convolutional Neural Networks (CNNs)**

- 10
- CNN Architecture
  - Convolutional Layers, Pooling
  - Applications in Image Processing

### **Recurrent Neural Networks (RNNs) & Long Short-Term Memory (LSTM)**

- 11
- RNN Structure
  - Time-series Data
  - LSTMs for Sequential Data

### **Reinforcement Learning**

- 12
- Markov Decision Processes (MDPs)
  - Q-Learning and Deep Q-Networks (DQNs)
  - Policy Gradient Methods

### **Natural Language Processing (NLP)**

- 13
- Text Preprocessing (Tokenization, Lemmatization)
  - Bag-of-Words, TF-IDF
  - Word Embeddings and Transformers

## Week Topics

- AI Ethics and Responsible AI**
- 14
- Bias in AI Models
  - Fairness, Accountability, and Transparency
  - AI in Society and Ethical Implications
- Capstone Project**
- 15
- Choose a real-world problem
  - Build an AI/ML solution using the concepts learned
  - Final presentation and evaluation
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## Grading & Evaluation

- **Assignments (30%):** Weekly coding exercises on ML models and AI concepts.
  - **Quizzes (10%):** Periodic quizzes to assess theoretical understanding.
  - **Midterm Exam (20%):** A written or coding exam covering the first half of the course.
  - **Final Project (30%):** A capstone project that integrates AI/ML concepts.
  - **Class Participation (10%):** Contribution to discussions and labs.
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## Textbooks and Resources

1. **Artificial Intelligence: A Modern Approach** by Stuart Russell and Peter Norvig
2. **Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow** by Aurélien Géron
3. **Deep Learning** by Ian Goodfellow, Yoshua Bengio, and Aaron Courville

## Tools & Platforms

- Python (Anaconda, Jupyter)
- Scikit-learn, TensorFlow, Keras, PyTorch
- Google Colab for cloud-based execution