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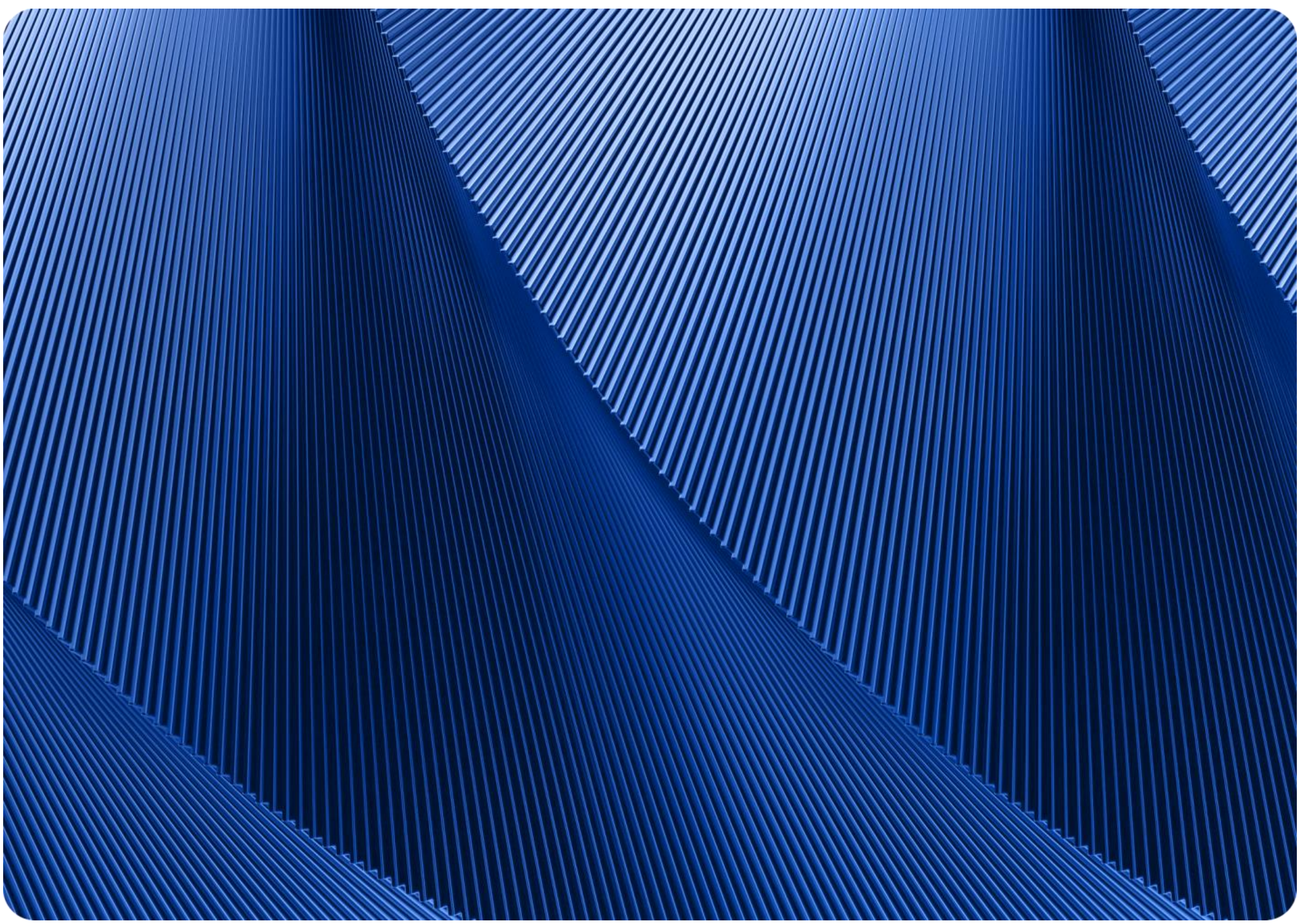
## Course Syllabus

# Introduction to Machine Learning

This introductory course provides hands-on experience with machine learning concepts, techniques, and real-world applications.



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# Course Description

This introductory course provides hands-on experience with machine learning concepts, techniques, and real-world applications. Students will explore fundamental topics including classification, training processes, inference, and linear regression through practical lab exercises and projects. The course emphasizes conceptual understanding and applied skills using industry-standard tools and environments. Students will progress from basic machine learning concepts to implementing solutions for automated decision-making tasks, building the foundational knowledge essential for careers in Applied Artificial Intelligence and pursue higher learning.

**Prerequisites:**
Python programming language

# Course Competencies

| Competency 1 |
|---|
| Summarize the fundamental concepts, terminology, and applications of machine learning, including supervised, unsupervised, and reinforcement learning paradigms and their real-world implementations |
| **Competency 2** |
| Differentiate among common machine learning algorithms, their appropriate use cases, and the trade-offs between different approaches for classification, regression, and clustering tasks |
| **Competency 3** |
| Apply machine learning tools and libraries (Python, Scikit-Learn, NumPy, Pandas, TensorFlow, AutoGluon) to implement complete ML solutions from data preparation through model deployment |
| **Competency 4** |
| Analyze datasets using exploratory data analysis techniques, feature engineering methods, and preprocessing strategies to prepare data for machine learning applications |

# Instructional Resources

No prescribed textbook is required due to the rapidly evolving nature of artificial intelligence tools, frameworks, and best practices. Instructors will curate up-to-date articles, tutorials, documentation, and other resources available to provide the latest advancements and diverse perspectives. This approach ensures flexibility to tailor content to class needs and incorporate emerging topics and industry practices.

**Platforms and Tools:**
Kaggle, GitHub, Google Colab, Amazon SageMaker, VS Code, Hugging Face

**Recommended Reading:**
See Course Bibliography/Materials section.

# Grading Schema

| Assignment Type | Percentage of Grade |
|---|---|
| General Assignments | 20% |
| Labs/Hands-On Activities | 25% |
| Midterm Project | 20% |
| Capstone Project | 25% |
| Course Portfolio | 10% |

# Supplemental Information

**General Assignments (20%)**

**Objective:** To reinforce theoretical concepts and develop analytical skills through weekly assignments including case studies, research discussions, problem sets, and design tasks directly related to module content.

**Labs/Hands-On Activities (25%)**

**Objective:** To provide students with practical understanding of Machine learning through guided implementation exercises, coding workshops, and interactive demonstrations using industry-standard tools and frameworks.

**Midterm Project (20%)**

**Objective**: Individual or group project demonstrating integration and application of knowledge from the first half of the course. Students will design and implement a focused Machine Learning solution addressing a specific problem or use case. Focus is on Exploratory Data Analysis: data processing, cleaning, feature engineering.

**Capstone Project (25%)**

**Objective**: To provide students with comprehensive hands-on experience in creating a practical, real-world application. Students will integrate multiple Machine Learning techniques learned throughout the course to develop an end-to-end solution with documentation and presentation. Focus in on building various models, comparing validation metrics, and recommending the best model for the chosen problem.

**Course Portfolio (10%)**

**Objective**: Individual dynamic document continuously updated and maintained on GitHub, serving as a comprehensive record of learning progress, code repositories, reflections, and achievements throughout the course. This portfolio demonstrates professional development and technical growth.

# Course Outline

| **Week starting on / Module** | **Module Topic** |
|---|---|
| Week 1 | Mod 01: Welcome, Introduction, and What is Machine Learning? |
| Week 2 | Mod 02: Tools Used in Machine Learning |
| Week 3 | Mod 03: Types of Machine Learning and Successful ML Solutions |
| Week 4 | Mod 04: ML Lifecycle, Overfitting, and Underfitting |
| Week 5 | Mod 05: AutoML and AutoGluon |
| Week 6 | Mod 06: Data in Machine Learning & Exploratory Data Analysis (EDA) |
| Week 7 | Mod 07: Basic Feature Engineering |
| Week 8 | Mod 08: Tree-Bades Models, Optimization, and Regularization |
| Week 9 | Mod 09: Hyperparameter Tuning |
| Week 10 | Mod 10: Ensembling (Bagging, Boosting, Stacking) |
| Week 11 | Mod 11: Introduction to Fairness and Bias Mitigation in ML |
| Week 12 | Mod 12: Fair Model Formulation and Metrics |
| Week 13 | Mod 13: Fairness Criteria |
| Week 14 | Mod 14: Bias Mitigation During Pre-processing, Training, and Post-Processing |
| Week 15 | Mod 15: Course Wrap-Up |
| Week 16 | Final Project/Final Exam |

# Course Bibliography/Materials

Babushkin, V. & Kravchenko, A. (2024). *Machine Learning System Design: with End-to-end Examples. Maning Publications*
*Recommended for part 2: Early Steps and Part 3: Intermediate Steps*

Quantum Technologies (2025). *Feature Engineering for Modern Machine Learning with Scikit-Learn*. Packt Publishing.
*Recommended for Modules 6, 7, and 8 for advanced data preparation techniques, feature engineering strategies, and pipeline automation.*

Taulli, T. (2024). *Machine Learning Engineering in Action*. Manning Publications.
*Recommended for Modules 4, 5, 9, and 15 for practical ML workflows, AutoML implementation, and production deployment considerations suitable for Applied AI students.*

Singh, A. & Gad, A. (2024). *Machine Learning Engineering with Python: Manage the Production Life Cycle of Machine Learning Models Using MLOps*. Packt Publishing.
*Recommended for Modules 2, 4, 14, and 15 for hands-on Python implementation, ML lifecycle management, and professional development practices.*

# Supplemental Papers (Optional)

Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., & Galstyan, A. (2021). A survey on bias and fairness in machine learning. *ACM Computing Surveys*, 54(6), 1-35.
*Recommended for Modules 11, 12, 13, and 14 for comprehensive coverage of bias detection, fairness metrics, and mitigation strategies.*

He, X., Zhao, K., & Chu, X. (2021). AutoML: A survey of the state-of-the-art. *Knowledge-Based Systems*, 212, 106622.
*Recommended for Module 5 for understanding AutoML principles, tools, and industry applications.*

Sculley, D., et al. (2015). Hidden technical debt in machine learning systems. *Advances in Neural Information Processing Systems*, 28, 2503-2511.
*Recommended for Modules 4 and 15 for understanding ML lifecycle challenges and production deployment considerations.*

Barocas, S., Hardt, M., & Narayanan, A. (2019). Fairness and Machine Learning: Limitations and Opportunities. MIT Press. (Selected chapters available online)
*Recommended for Modules 11-14 for theoretical foundations and practical approaches to algorithmic fairness.*

Instructors may consider adopting these books and papers to complement curated resources, aligning with course objectives, SLOs, and teaching style.