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# Scientific Machine Learning and Data-Driven Methods in Engineering

**Programme Duration:** 15 Hours
**Programme Structure:** 5 Main Modules (3 Hours each)
**Delivery Mode:** Executive / Continuing Education (Blended: Lectures + Hands-on Labs)
**Instructor:** Prof. Andrew Ooi, Department of Mechanical Engineering, The University of Melbourne

## 1. Programme Overview

Modern engineering practice is undergoing a paradigm shift driven by the convergence of classical physics-based modeling and data-driven artificial intelligence techniques. While Computational physics and numerical simulations remain foundational, their limitations in handling high-dimensional, uncertain, and data-rich systems necessitate new approaches. Scientific Machine Learning (SciML) provides a rigorous framework to integrate physical laws, domain knowledge, and modern machine learning techniques into next-generation engineering models.

This course is designed to equip participants with practical and conceptual tools to blend scientific principles with data-driven modeling, enabling faster, more accurate, and more reliable engineering decision-making. The course program emphasizes hands-on learning using the Julia programming language, widely recognized for high-performance scientific computing.

## 2. Programme Objectives

Upon completion of this programme, participants will be able to: - Understand the limitations of purely physics-based and purely data-driven models - Apply optimization techniques to engineering problems using modern computational tools - Develop and train neural networks for scientific and engineering applications - Integrate physical laws with data-driven models using physics-informed approaches - Implement Neural Ordinary Differential Equations (Neural ODEs) for continuous-time dynamical systems - Critically evaluate uncertainty, robustness, and reliability of machine-learning-assisted engineering models

## 3. Target Participants

This course is intended for: - Engineering professionals in R&D, design, and analytics roles - Students transitioning to data-driven modeling - Doctoral scholars and postdoctoral researchers - Technology leaders seeking strategic understanding of AI-enabled engineering

A working knowledge of undergraduate-level mathematics and engineering fundamentals is assumed.

# 4. Detailed Programme Structure (Module-wise and Sub-Module-wise)

## Module-wise and Sub-Module-wise Breakdown

| Main Module | Sub-Module (30 min each) | Title | Key Focus |
|---|---|---|---|
| **Module 1: Foundations – Julia & Optimization** | 1.1 | Course Orientation & Motivation | Role of SciML in modern engineering |
| | 1.2 | Julia Ecosystem | Julia, VSCode, Jupyter workflows |
| | 1.3 | Julia Programming Basics | Scientific coding fundamentals |
| | 1.4 | Numerical Performance | Efficient and scalable computation |
| | 1.5 | Optimization Formulation | Engineering objective functions |
| | 1.6 | Basic Optimization in Julia | Hands-on implementation |
| **Module 2: Optimization Techniques** | 2.1 | Optimization Recap | Linking computation and ML |
| | 2.2 | Gradient-Based Methods | Sensitivities and gradients |
| | 2.3 | Optimization Algorithms | Convergence and stability |
| | 2.4 | Automatic Differentiation | Accurate gradient |

| Main Module | Sub-Module (30 min each) | Title | Key Focus |
|---|---|---|---|
| | | | computation |
| | 2.5 | Optimization Lab | Multi-parameter problems |
| **Module 3: Curve Fitting & Neural Networks** | 3.1 | Engineering Regression | Noise and overfitting |
| | 3.2 | Multivariable Curve Fitting | High-dimensional data |
| | 3.3 | Introduction to Neural Networks | Motivation and theory |
| | 3.4 | Network Architecture | Layers and activations |
| | 3.5 | Training Neural Networks | Backpropagation and loss |
| | 3.6 | Neural Network Lab | Scientific ML examples |
| **Module 4: Physics-Informed Learning** | 4.1 | Limits of Black-Box ML | Trust and interpretability |
| | 4.2 | Embedding Physical Laws | Conservation principles |
| | 4.3 | Physics-Informed Neural Networks | PINN framework |
| | 4.4 | Hybrid Modeling | Data + simulations |
| | 4.5 | Engineering Case Studies | Fluids, solids, transport |
| | 4.6 | Hybrid Modeling Lab | Physics-aware ML |
| **Module 5: Neural ODEs & Outlook** | 5.1 | Motivation for Neural ODEs | Continuous-time dynamics |

| Main Module | Sub-Module (30 min each) | Title | Key Focus |
|---|---|---|---|
| | 5.2 | Mathematical Foundations | ODE solvers and ML |
| | 5.3 | Neural ODE Implementation | Julia-based implementation |
| | 5.4 | Engineering Applications | Mechanics and dynamics |
| | 5.5 | Uncertainty Quantification | Sensitivity and robustness |
| | 5.6 | Course Wrap-Up | Future directions and assessment |

## 5. Learning Outcomes and Bloom's Taxonomy Mapping

| Learning Outcome | Bloom's Level |
|---|---|
| Explain the principles of Scientific Machine Learning | Understand |
| Apply optimization techniques to engineering problems | Apply |
| Develop data-driven and hybrid ML models | Apply / Analyze |
| Analyze model behavior using physical constraints | Analyze |
| Design physics-informed neural networks | Create |
| Evaluate robustness and uncertainty in ML models | Evaluate |

## 6. Assessment Framework

Assessment is designed to be participant-friendly, application-oriented, and aligned with executive learning objectives.

### Assessment Components

| Component | Weightage | Description |
|---|---|---|
| Hands-on Assignments | 50% | Short problem-based tasks at the end of each main module |
| Capstone Mini-Project | 30% | End-to-end modeling of an engineering problem using SciML |
| Participation & Engagement | 20% | In-class interaction, coding exercises, discussions |

## 7. **Participant-Friendly Assessment Framework**

### Hands-on Assignments

| Criterion | Excellent (A) | Good (B) | Satisfactory (C) |
|---|---|---|---|
| Problem Understanding | Clear formulation and assumptions | Minor gaps | Basic understanding |
| Technical Implementation | Correct, efficient, well-documented code | Minor errors | Functional but limited |
| Scientific Reasoning | Strong link to physical principles | Partial linkage | Minimal reasoning |

### Capstone Mini-Project

| Criterion | Excellent | Good | Satisfactory |
|---|---|---|---|
| Problem Selection | Realistic, well-motivated | Moderately scoped | Simple problem |
| Model Design | Innovative hybrid/physics-informed model | Standard ML model | Basic data-driven model |
| Interpretation | Insightful physical interpretation | Reasonable discussion | Limited interpretation |
| Presentation | Clear, concise, professional | Adequate | Minimal clarity |

## 8. Certification

Participants who successfully complete the programme and meet assessment criteria will receive an **Executive Education Certificate**.

## 9. Programme Value Proposition

This programme uniquely positions participants at the intersection of engineering science, computation, and artificial intelligence, enabling them to lead innovation in academia, industry, and policy-driven technology development.

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