UNIVERSITY OF LONDON

Complex problem-solving

Decision making

Digital Skills

Course information 2026-27

ST3189 Machine Learning

General information

MODULE LEVEL: 6

CREDIT: 30

NOTIONAL STUDY TIME: 300 hours

MODE: Locally Taught, Independent Learner Route and Online Taught

Summary

In the last decade there has been a remarkable growth in machine learning with image and speech recognition, recommendation systems and artificial intelligence being only some of the big success stories. Following recent advances in gathering, storing and managing vast amounts of observations, the ability to process high dimensional data and deal with uncertainty becomes increasingly important. Despite the increase of available information, inference may still lead to false conclusions in the absence of a suitable methodology. This course covers a wider range of such model based and algorithmic machine learning methods, illustrated in various real-world applications and datasets. At the same time, the theoretical foundation of the methodology is presented.

Conditions

Please refer to the relevant programme structure in the EMFSS Programme Regulations to check:

- where this course can be placed on your degree structure; and
- details of prerequisites and corequisites for this course.

You should also refer to the Exclusions list in the EMFSS Programme Regulations to check if any exclusions apply for this course.

Aims and objectives

- To provide an in-depth introduction to supervised and unsupervised learning.
- To present the main models and algorithms for regression, classification and clustering.
- To provide the opportunity to students to apply and evaluate suitable methods on real datasets and assess their predictive performance.

Learning outcomes

At the end of this half course and having completed the essential reading and activities students should be able to:

- develop an understanding of the process to learn from data.
- be familiar with a wide variety of algorithmic and model based methods to extract information from data.
- apply and evaluate suitable methods to various datasets by model selection and predictive performance evaluation.
- gain knowledge and experience on conducting machine learning in R or Python.

Employability skills

Below are the three most relevant employability skills that students acquire by undertaking this course which can be conveyed to future prospective employers:

1. Complex problem solving
2. Decision making
3. Digital Skills

Essential reading

Essential reading:
James G., Witten D., Hastie T. and Tibshirani R. An introduction to Statistical Learning: with Applications in R, Springer (2014).

Further reading:
Bishop C.M. Pattern recognition and machine learning. Springer (2006)

Murphy K.P. Machine learning: A probabilistic perspective. MIT Press, second edition (2012)

Assessment

This course is assessed by an individual case study piece of coursework (30%) and a three-hour and fifteen-minute closed-book written examination (70%).

Syllabus

This is a description of the material to be examined, as published in the Regulations. On registration, students will receive a detailed subject guide which provides a framework for covering the topics in the syllabus and directions to the essential reading.

Introduction to machine learning concepts: Machine learning model, cost function, train and test error, overfit, bias-variance trade-off, cross validation, machine learning pipelines.

Linear regression and frequentist inference: Linear regression model, polynomial regression, general linear model, linear basis functions. Estimators, likelihood function, maximum likelihood estimates, bias variance and meaning squared error of estimators asymptotic optimality of MLEs, confidence intervals, hypothesis testing and p-values, frequentist inference for linear regression. Regression output, assumptions and limitations of linear regression.

Bayesian Inference: Elements of Bayesian inference, prior and posterior distribution, conjugate models, Bayes estimators, credible intervals, model evidence, Bayes factors, posterior-predictive distributions, Monte Carlo for Bayesian inference, Laplace approximation.

Linear Regression-shrinkage methods and model selection: Forward, Backward Stepwise selections, best subset selection, Lasso regression, ridge regression, elastic net, Bayesian linear regression.

Linear models for classification: Introduction to classification, logistic regression, maximum likelihood for logistic regression, gradient descent and Newton Raphson algorithms, penalised and Bayesian logistic regression, generative models, linear and quadratic discriminant analysis, evaluation of classification models, application to natural language processing.

Unsupervised learning: Hierarchical clustering, k-means, mixture models, dimension reduction, principal components and factor analysis.

Regression and classification trees: Interpretation of a tree, recursive binary splitting, classification trees, tree pruning.

Ensemble Learning: Majority voting, Bagging, Boosting, model averaging, stacking, bagging trees and random forests, boosting trees.

Neural networks: Introduction to neural networks, single layer and multi-layer perceptron, architecture of neural networks, activation functions, deep neural networks, fitting neural networks, stochastic gradient descent algorithm, backpropagation.

Learning functions: Cubic splines, smoothing splines, kernels, Gaussian processes, Gaussian process regression and classification.