Mathematics and Statistics Undergraduate Handbook
Supplement to the Handbook

Honour School of Mathematics and Statistics
Syllabus and Synopses for Part C 2026–2027
for examination in 2027

Contents

Every effort is made to ensure that the list of courses offered is accurate at the time of going online. However, students are advised to check the up-to-date version of this document on the Department of Statistics website.

Notice of misprints or errors of any kind, and suggestions for improvements in this booklet should be addressed to the Academic Administrator in the Department of Statistics, academic.administrator@stats.ox.ac.uk.

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1 Honour School of Mathematics and Statistics

1.1 Units

See the current edition of the Examination Regulations at https://examregs.admin.ox.ac.uk for the full regulations governing these examinations. The examination conventions can be found on the Canvas course site.

In Part C,

- each candidate shall offer a minimum of six units and a maximum of eight units from the schedule of units for Part C
- and each candidate shall also offer **a dissertation** on a statistics project (equivalent of 2 units).
- At least 4 of the units taken by Part C students must be assessed by written examination.

At least **two** units should be from the schedule of 'Statistics' units.
The USMs for the dissertation and the best six units will count for the final classification.

Units from the schedule of 'Mathematics Department units' for Part C of the Honour School of Mathematics are also available – see Section 3.

This booklet describes the units available in Part C. Information about dissertations/ statistics projects will be available on the Department of Statistics Canvas site.

All of the units described in this booklet are "M-level".

Students are asked to register for the options they intend to take by the end of week 10, Trinity Term 2026 using the Mathematical Institute course management portal. https://www.maths.ox.ac.uk/members/students/undergraduate-courses/teaching-and-learning/course-registration. Students may alter the options they have registered for after this but it is helpful if their registration is as accurate as possible. Students will then be asked to sign up for classes at the start of Michaelmas Term 2026. Students who register for a course or courses for which there is a quota should consider registering for an additional course (by way of a "reserve choice") in case they do not receive a place on the course with the quota.

Every effort will be made when timetabling lectures to ensure that mathematics lectures do not clash. However, because of the large number of options this may sometimes be unavoidable.

1.2 Part C courses in future years

In any year, most courses available in Part C that year will normally also be available in Part C the following year. However, sometimes new options will be added or existing options may cease to run. The list of courses that will be available in Part C in any year will be published by the end of the preceding Trinity Term.

1.3 Course list by term

The 2026-2027 list of Part C courses by term is:

Michaelmas Term

SC1 Stochastic Models in Mathematical Genetics
SC2 Probability and Statistics for Network Analysis
SC7 Bayes Methods
SC9 Probability on Graphs and Lattices
SC10 Algorithmic Foundations of Learning

Hilary Term

SC4 Advanced Topics in Statistical Machine Learning
SC5 Advanced Simulation Methods
SC11 Climate Statistics
C8.4 Probabilistic Combinatorics.

2. Statistics Units

2.1 **SC1 Stochastic Models in Mathematical Genetics –** 16 MT

Level: M-level
Method of Assessment: written examination
Weight: Unit

Recommended Prerequisites
Part A A8 Probability.
SB3.1 Applied Probability would be helpful.

Aims & Objectives
The aim of the lectures is to introduce modern stochastic models in mathematical population genetics and give examples of real world applications of these models. Stochastic and graph theoretic properties of coalescent and genealogical trees are studied in the first eight lectures. Diffusion processes and extensions to model additional key biological phenomena are studied in the second eight lectures.

Synopsis
Evolutionary models in Mathematical Genetics:
The Wright-Fisher model. The Genealogical Markov chain describing the number ancestors back in time of a collection of DNA sequences.

The Coalescent process describing the stochastic behaviour of the ancestral tree of a collection of DNA sequences. Mutations on ancestral lineages in a coalescent tree. Models with a variable population size.

The frequency spectrum and age of a mutation. Ewens' sampling formula for the probability distribution of the allele configuration of DNA sequences in a sample in the infinitely-many-alleles model. Hoppe's urn model for the infinitely-many-alleles model.

The infinitely-many-sites model of mutations on DNA sequences. Gene trees as perfect phylogenies describing the mutation history of a sample of DNA sequences. Graph theoretic constructions and characterizations of gene trees from DNA sequence variation. Gusfield's construction algorithm of a tree from DNA sequences. Examples of gene trees from data.

Modelling biological forces in Population Genetics: Recombination. The effect of recombination on genealogies. Detecting recombination events under the infinitely-many-sites model. Hudson's algorithm. Haplotype bounds on recombination events. Modelling recombination in the Wright-Fisher model. The coalescent process with recombination: the ancestral recombination graph. Properties of the ancestral recombination graph.

Introduction to diffusion theory. Tracking mutations forward in time in the Wright-Fisher model. Modelling the frequency of a neutral mutation in the population via a diffusion process limit. The generator of a diffusion process with two allelic types. The probability of fixation of a mutation. Genic selection. Extension of results from neutral to selection case. Behaviour of selected mutations.

Reading
R. Durrett, *Probability Models for DNA Sequence Evolution*, Springer, 2008

A.Etheridge, Some Mathematical Models from Population Genetics. Ecole d'Eté de Probabilities de Saint-Flour XXXIX-2009, Lecture Notes in Mathematics, 2012
W. J. Ewens, *Mathematical Population Genetics,* 2nd Ed, Springer, 2004
J. R. Norris, *Markov Chains*, Cambridge University Press, 1999
M. Slatkin and M. Veuille, *Modern Developments in Theoretical Population Genetics*, Oxford Biology, 2002
S. Tavaré and O. Zeitouni, *Lectures on Probability Theory and Statistics, Ecole d'Eté de Probabilities de Saint-Flour XXXI - 2001*, Lecture Notes in Mathematics 1837, Springer, 2004

2.2 **SC2 Probability and Statistics for Network Analysis** – 16 MT

Level: M-level
Method of Assessment: Written examination
Weight: Unit

For this course, 2 lectures and 2 intercollegiate classes are replaced by 2 practical classes. (The total time for this course is the same as for other Part C courses.)

Recommended prerequisites
Part A A8 Probability and A9 Statistics

Aims and Objectives
Many data come in the form of networks, for example friendship data and protein-protein interaction data. As the data usually cannot be modelled using simple independence assumptions, their statistical analysis provides many challenges. The course will give an introduction to the main problems and the main statistical techniques used in this field. The techniques are applicable to a wide range of complex problems. The statistical analysis benefits from insights which stem from probabilistic modelling, and the course will combine both aspects.

Synopsis
Exploratory analysis of networks. The need for network summaries. Degree distribution, clustering coefficient, shortest path length. Motifs. Spectral summaries.

Probabilistic models: Bernoulli random graphs, geometric random graphs, preferential attachment models, small world networks, inhomogeneous random graphs, exponential random graphs.

Small subgraphs: Stein's method for normal and Poisson approximation. Branching process approximations, threshold behaviour, shortest path between two vertices.

Statistical analysis of networks: Sampling from networks. Parameter estimation for models. Inferring edges in networks. Network comparison. A brief look at community detection. A brief look at graph neural networks.

Reading
A.D. Barbour and G. Reinert, Networks: Probability and Statistics. Cambridge University Press, 2026
R. Durrett, Dynamics on Graphs, Springer Nature Switzerland, 2026.
E.D Kolaczyk and G. Csádi, *Statistical Analysis of Network Data with R*, Springer, 2014
M. Newman, *Networks*. Oxford University Press, 2018

2.3 **SC4 Advanced Topics in Statistical Machine Learning** – 16 HT

Level: M-level
Methods of Assessment: written examination.
Weight: Unit

Recommended prerequisites
The course requires a good level of mathematical maturity. Students are expected to be familiar with core concepts in statistics (regression models, bias-variance tradeoff, Bayesian inference), probability (multivariate distributions, conditioning) and linear algebra (matrix-vector operations, eigenvalues and eigenvectors). Previous exposure to machine learning (empirical risk minimisation, dimensionality reduction, overfitting, regularisation) is highly recommended.
Students would also benefit from being familiar with the material covered in the following courses offered in the Statistics department: SB2.1 Foundations of Statistical Inference and in SB2.2 Statistical Machine Learning.

Aims and Objectives
Machine learning (ML) is a core technology widely used across the sciences, engineering, and society, enabling pattern discovery and accurate prediction from large datasets. This course focuses on statistical machine learning, highlighting the probabilistic foundations that underpin modern ML approaches, including artificial intelligence (AI). The course studies both unsupervised and supervised learning. Several advanced and state-of-the-art topics, such as large language models (LLMs), are covered in detail. The course also covers computational considerations of machine learning algorithms and how they can scale to large datasets.

Synopsis
- Empirical risk minimisation. Loss functions. Generalization. Over- and underfitting. Regularisation.
- Support vector machines.
- Kernel methods and reproducing kernel Hilbert spaces. Representer theorem. Representation of probabilities in RKHS.
- Probabilistic machine learning: fundamentals of Bayesian inference.
- Variational inference, amortized variational inference.
- Gaussian processes
- Deep learning fundamentals: neural networks; automatic differentiation; stochastic gradient descent.
- Large language models: transformers, pre-training, scaling laws, post-training, evaluation

Software
Knowledge of Python is not required for this course, but some examples may be done in Python. Students interested in learning Python are referred to the following free University IT online course, which should ideally be taken before the beginning of this course: https://skills.it.ox.ac.uk/whats-on#/course/LY046

Reading
C. Bishop, Pattern Recognition and Machine Learning, Springer,2007
K. Murphy, Machine Learning: A Probabilistic Perspective, MIT Press, 2012

Further Reading
T. Hastie, R. Tibshirani, J Friedman, Elements of Statistical Learning, Springer, 2009

Scikit-learn: Machine Learning in Python, Pedregosa et al., JMLR 12, pp. 2825-2830, 2011, http://scikit-learn.org/stable/tutorial/

2.4 **SC5 Advanced Simulation Methods** - 16 HT

Level: M-level
Methods of Assessment: This course is assessed by written examination.
Weight: Unit

Recommended Prerequisites
The course requires a good level of mathematical maturity as well as some statistical intuition and background knowledge to motivate the course. Students are expected to be familiar with core concepts from probability (conditional probability, conditional densities, properties of conditional expectations, basic inequalities such as Markov's, Chebyshev's and Cauchy-Schwarz's, modes of convergence), basic limit theorems from probability in particular the strong law of large numbers and the central limit theorem, Markov chains, aperiodicity, irreducibility, stationary distributions, reversibility and convergence. Most of these concepts are covered in courses offered in the Statistics department, in particular prelims probability, A8 probability and SB3.1 (formerly SB3a) Applied Probability. Familiarity with basic Monte Carlo methods will be helpful, as for example covered in A12 Simulation and Statistical Programming.
Some familiarity with concepts from Bayesian inference such as posterior distributions will be useful in order to understand the motivation behind the material of the course.

Aims and Objectives
The aim of the lectures is to introduce modern simulation methods.
This course concentrates on Markov chain Monte Carlo (MCMC) methods and Sequential Monte Carlo (SMC) methods. Examples of applications of these methods to complex inference problems will be given.

Synopsis
Classical methods: inversion, rejection, composition.

Importance sampling.

MCMC methods: elements of discrete-time general state-space Markov chains theory, Metropolis-Hastings algorithm.

Advanced MCMC methods: Gibbs sampling, slice sampling, tempering/annealing, Hamiltonian (or Hybrid) Monte Carlo, pseudo-marginal MCMC.

Sequential importance sampling.

SMC methods: nonlinear filtering.

Reading
C.P. Robert and G. Casella, *Monte Carlo Statistical Methods*, 2nd edition, Springer-Verlag, 2004

Further reading
J.S. Liu, *Monte Carlo Strategies in Scientific Computing*, Springer-Verlag, 2001

2.5 **SC7 Bayes Methods** – 16 MT

Level: M-level
Method of Assessment: Written examination
Weight: Unit

Recommended prerequisites
SB2.1 Foundations of Statistical Inference is desirable, of which 6 lectures on Bayesian inference, decision theory and hypothesis testing with loss functions are assumed knowledge. A12 Simulation and Statistical Programming desirable.

Synopsis
Theory: Decision-theoretic foundations, Savage axioms. Prior elicitation, exchangeability. Bayesian Non-Parametric (BNP) methods, the Dirichlet process and the Chinese Restaurant Process. Asymptotics, and information criteria.

Computational methods: Bayesian inference via MCMC; Estimation of marginal likelihood; Approximate Bayesian Computation and intractable likelihoods; reversible jump MCMC.

Case Studies: extend understanding of prior elicitation, BNP methods and asymptotics through a small number of substantial examples. Examples to further illustrate building statistical models, model choice, model averaging and model assessment, and the use of Monte Carlo methods for inference.

Reading
C.P. Robert, *The Bayesian Choice: From Decision-Theoretic Foundations to Computational Implementation*, 2nd edition, Springer, 2001

Further Reading
A. Gelman et al, *Bayesian Data Analysis*, 3rd edition, Boca Raton Florida: CRC Press, 2014
P Hoff, *A First Course in Bayesian Statistical Methods,* Springer, 2010
DeGroot, Morris H., *Optimal Statistical Decisions.* Wiley Classics Library. 2004.

2.6 **SC9 Probability on Graphs and Lattices** – 16 MT

Level: M-level
Method of Assessment: Written examination Weight: Unit

Recommended Prerequisites

Discrete and continuous time Markov processes on countable state space, as covered for example in Part A A8 Probability and Part B SB3.1 Applied Probability.

Aims and Objectives

The aim is to introduce fundamental probabilistic and combinatorial tools, as well as key models, in the theory of discrete disordered systems. We will examine the large-scale behaviour of systems containing many interacting components, subject to some random noise. Models of this type have a wealth of applications in statistical physics, biology and beyond, and we will see several key examples in the course. Many of the tools we will discuss are also of independent theoretical interest, and have far reaching applications. For example, we will study the amount of time it takes for a random system to reach its stationary distribution (mixing time). This concept is also important in many statistical applications, such as studying the run time of MCMC methods.

Synopsis

- Uniform spanning trees, loop-erased random walks, Wilson's algorithm, the Aldous-Broder algorithm.
- Percolation, phase transitions in Z^d, specific tools in Z^2.
- Ising model, random-cluster model and other models from statistical mechanics (e.g. Potts model, hard-core model).
- Glauber dynamics, mixing times, couplings.

Reading

- G. Grimmett, *Probability on graphs: random processes on graphs and lattices*, Cambridge University Press, 2010; 2017 (2^{nd} edition).
- B. Bollobás, O. Riordan, *Percolation*, Cambridge University Press, 2006.
- T. Liggett, *Continuous time Markov processes: an introduction*, American Mathematical Society, 2010.
- D. A. Levin, Y. Peres, E. L. Wilmer, *Markov chains and mixing times*, American Mathematical Society, 2009.
- H. Duminil-Copin, *Introduction to Bernoulli percolation*. Lecture notes available online at https://www.ihes.fr/~duminil/publi/2017percolation.pdf.

2.7 SC10 **Algorithmic Foundations of Learning** – 16 MT

Level: M-level
Method of Assessment: Written examination
Weight: Unit

Recommended Prerequisites
The course requires a good level of mathematical maturity, and assumes familiarity with concepts from introductory-level analysis, probability theory and linear algebra.

Students from nonmathematical backgrounds interested in taking the course would benefit from carefully studying chapters 2 and 3 of Lattimore & Szepesvári 2020 ahead of time.

Previous exposure to machine learning or statistical theory is not required.

Aims and objectives
The course provides a brief introduction to the main areas of research in the theory of machine learning, and to the tools used to carry out such research.

Synopsis

- High-dimensional probability: moment-based concentration inequalities; covering, packing and chaining; the martingale method; concentration via nonnegative supermartingales. Examples in random vectors, matrices and processes.

- Statistical learning theory: empirical risk minimisation; learning via uniform convergence; slow & fast rates; Rademacher complexity & VC theory; minimax lower bounds. Examples in linear, generalised-linear and kernel-based predictors.

- Optimisation, online learning & reinforcement learning: gradient descent algorithm and variants; exponential weights algorithm; boosting. Explore-then commit & upper-confidence-bounds algorithms for stochastic bandits; basics of planning in Markov Decision processes.

Reading

- Shai Shalev-Shwartz and Shai Ben-David. Understanding Machine Learning: From Theory to Algorithms. Cambridge University Press. 2014
- Martin J. Wainwright. High-Dimensional Statistics. A Non-Asymptotic Viewpoint. Cambridge University Press. 2019.
- Orabona F. A modern introduction to online learning. Lecture notes available online at https://arxiv.org/pdf/1912.13213. 2019.
- Tor Lattimore and Csaba Szepesvári. Bandit Algorithms. Book available online at https://tor-lattimore.com/downloads/book/book.pdf. 2019.

2.8 SC11 **Climate Statistics** – 16 HT

Level: M-level
Method of Assessment: Written examination
Weight: Unit

Recommended Prerequisites:

This course draws on a range of statistical methods, and students should expect that some topics will be more familiar than others. Background material and references will be provided where specialised methods are needed.
Students should have a good grounding in probability and statistical theory at least at the level of Oxford's Part A probability and statistics. They should be comfortable with expectation, variance, covariance, conditional distributions, limit theorems, likelihood, confidence intervals, hypothesis testing, and regression models.
Familiarity with model selection is assumed. In particular, students should understand overfitting, the bias-variance tradeoff, cross-validation, residual diagnostics, and information criteria such as AIC and BIC. These ideas will be reviewed in the course, but mainly as background for their use in climate-science examples.
Linear algebra will be used throughout the course, especially in the multivariate sections. Students should be comfortable with vectors, matrices, eigenvalues and eigenvectors, orthogonality, projections, and covariance matrices. Some familiarity with singular value decomposition is helpful, but the relevant ideas will be reviewed.
The course will introduce the necessary ideas behind ARMA models, state-space models, spectral methods, principal components, canonical correlation analysis, forecasting, and extreme value methods, but students will benefit from some prior statistical modelling experience. Familiarity with generalised linear models, mixed models, and simulation-based inference may be useful for some examples, but will not be assumed as core background.
Fourier methods will be used in the time-series part of the course. They will be developed from the beginning, but students should be comfortable with complex numbers, exponentials, and trigonometric functions (on the level of the first-year 2-

lecture Oxford course Introduction to Complex Numbers). Complex analysis is not required.
The notes use R for examples and data analysis. Students are encouraged to familiarise themselves with basic R syntax, but they will not be examined on writing code.

Aims and Objectives

This course aims to teach the fundamentals of some statistical concepts and techniques that are relevant for understanding and carrying out research in climate science. It will introduce the main varieties of climate data, demonstrate how they can be analysed with these techniques, and explain core concepts of climate science, showing how advances in the field have paralleled advances in statistical methodology.
The main topics covered are core statistical methods, presented in the context of their applications to climate science. The topics are: the nature of climate data; time series (time domain and frequency domain); multivariate analysis, multivariate decomposition methods (PCA, CCA, related issues), and extreme values; predictive statistics.

Computing

Techniques of data analysis in R will be taught, and students will be expected to engage with issues of data analysis. Students are encouraged to familiarise themselves with the basic syntax of R, so that they can interpret the code examples included in the lecture notes. The problem sheets will include computing questions, which may in principle be done in any programming language, though solutions will be provided only in R. Students will not be examined on writing code, but on the interpretation of computational outputs.

Synopsis

Background and orientation:
• Historical background to climate science;
• Climate models, model selection, prediction, and uncertainty;
• Exploratory data analysis, smoothing, and decomposition.

Climate data:
• Observational, palaeoclimate, reanalysis, and model-based climate data;
• Spatial and temporal structure of climate records;
• Examples including temperature anomalies, atmospheric carbon dioxide, and long instrumental records.

Time series:
• Stationarity, autocorrelation, and ARMA/ARIMA models;
• State-space models and the Kalman filter;
• Regression with autocorrelated errors and spurious correlation;
• Spectral methods, filtering, and analysis across timescales.

Multivariate climate statistics:
• Principal components analysis and empirical orthogonal functions;
• Canonical correlation analysis and related dimension-reduction methods;
• Multivariate methods for spatial climate fields, teleconnections, & reconstruction.

Prediction and forecasting:
• Forecast skill and verification;

• Predictability and predictable components;
• Ensemble forecasting and probabilistic prediction.

Extreme values and attribution:
• Extreme value distributions, return levels, and threshold methods;
• Non-stationary extremes in a changing climate;
• Statistical approaches to extreme-event attribution.

Reading

- DelSole and Tippett, Statistical Methods for Climate Scientists, is the closest general companion to the course, especially for climate data, EOFs, CCA, prediction, and forecast skill.
- Shumway and Stoffer, Time Series Analysis and Its Applications, is a useful reference for ARMA/ARIMA models, state-space models, the Kalman filter, and spectral methods.

Further Reading:

- Daniel S. Wilks, Statistical Methods in the Atmospheric Sciences , gives a broader and more applied treatment of statistical methods used in meteorology and climatescience.
- Eli Tziperman, Global Warming Science, gives accessible physical background on the climate system, climate sensitivity, feedbacks, and internal variability.
- Spencer Weart, The Discovery of Global Warming, is recommended for historical context on the development of climate science. It is available as a free web resource: https://history.aip.org/climate/index.htm.
- “Quantification and interpretation of the climate variability record.” Anna S. von der Heydt, et al. Global and Planetary Change 197 (2021): 103399.
- P. J. Brockwell and R. A. Davis, Time Series: Theory and Methods, gives a more mathematical treatment of stationary time series, ARMA models, prediction, and spectral theory.
- J. Durbin and S. J. Koopman, Time Series Analysis by State Space Methods, is the standard advanced reference for state-space modelling and Kalman filtering.
- C. Torrence and G. P. Compo, “A practical guide to wavelet analysis”, Bulletin of the American Meteorological Society 79.1 (1998): 61–78 is a useful applied reference for the wavelet material.
- S. Coles, An Introduction to Statistical Modeling of Extreme Values, is a compact reference for the extreme-value theory used in the course.
- Stott et al., “Attribution of extreme weather and climate-related events”, Wiley Interdisciplinary Reviews: Climate Change 7.1 (2016): 23-41, gives an accessible overview of extreme-event attribution and the probability-ratio/fraction-attributable-risk frame-work.
- R. Hyndman Forecasting: Principles and practice, https://otexts.com/fpp3/.

2.9 **C8.4 Probabilistic Combinatorics -** 16 HT

Level: M-level
Method of Assessment: Written examination.
Weight: Unit

Recommended Prerequisites:

B8.5 Graph Theory and A8: Probability. C8.3 Combinatorics is not as essential prerequisite for this course, though it is a natural companion for it.

Overview
Probabilistic combinatorics is a very active field of mathematics, with connections to other areas such as computer science and statistical physics. Probabilistic methods are essential for the study of random discrete structures and for the analysis of algorithms, but they can also provide a powerful and beautiful approach for answering deterministic questions. The aim of this course is to introduce some fundamental probabilistic tools and present a few applications.

Learning Outcomes
The student will have developed an appreciation of probabilistic methods in discrete mathematics.

Synopsis
First-moment method, with applications to Ramsey numbers, and to graphs of high girth and high chromatic number.
Second-moment method, threshold functions for random graphs.
Lovász Local Lemma, with applications to two-colourings of hypergraphs, and to Ramsey numbers.
Chernoff bounds, concentration of measure, Janson's inequality.
Branching processes and the phase transition in random graphs.
Clique and chromatic numbers of random graphs.

Reading
N. Alon and J.H. Spencer, *The Probabilistic Method*, 3rd edition, Wiley, 2008

Further Reading:
B. Bollobás, *Random Graphs*, 2nd edition, Cambridge University Press, 2001
M. Habib, C. McDiarmid, J. Ramirez-Alfonsin, B. Reed, ed., *Probabilistic Methods for Algorithmic Discrete Mathematics,* Springer, 1998
S. Janson, T. Luczak and A. Rucinski, *Random Graphs,* John Wiley and Sons, 2000
M. Mitzenmacher and E. Upfal, *Probability and Computing: Randomized Algorithms and Probabilistic Analysis,* Cambridge University Press, New York (NY), 2005
M. Molloy and B. Reed, *Graph Colouring and the Probabilistic Method,* Springer, 2002
R. Motwani and P. Raghavan, *Randomized Algorithms,* Cambridge University Press, 1995

3 Mathematics units

The Mathematics units that students may take are drawn from Part C of the Honour School of Mathematics. For full details of these units, see the Syllabus and Synopses for Part C of the Honour School of Mathematics, which are available on the web at https://courses.maths.ox.ac.uk/course/index.php?categoryid=961

The Mathematics units that are available are as follows:

C1.1	Model Theory	16 MT
C1.2	Godel's Incompleteness Theorems	16 HT
C1.3	Analytic Topology	16 HT
C1.4	Axiomatic Set Theory	16 MT
C2.2	Homological Algebra	16 MT
C2.4	Infinite Groups	16 MT
C2.5	Non-Commutative Rings	16 HT
C2.6	Introduction to Schemes	16 HT
C2.7	Category Theory	16 MT
C3.1	Algebraic Topology	16 MT
C3.2	Geometric Group Theory	16 HT
C3.3	Differentiable Manifolds	16 MT
C3.4	Algebraic Geometry	16 MT
C3.5	Lie Groups	16 HT
C3.7	Elliptic Curves	16 HT
C3.8	Analytic Number Theory	16 MT
C3.9	Computational Algebraic Topology	16 HT
C3.10	Additive Number Theory	16 MT
C3.11	Riemannian Geometry	16 HT
C3.12	Low-Dimensional Topology and Knot Theory	16 HT
C4.1	Further Functional Analysis	16 MT
C4.3	Functional Analytic Methods for PDEs	16 MT
C4.6	Fixed Point Methods for Nonlinear PDEs	16 HT
C4.7	Fourier Analysis	16 MT
C4.9	Optimal Transport and Partial Differential Equations	16 HT
C4.10	Operator Algebras	16 HT
C5.1	Solid Mechanics	16 MT
C5.2	Elasticity and Plasticity	16 HT
C5.4	Networks	16 HT
C5.5	Perturbation Methods	16 HT
C5.6	Applied Complex Variables	16 MT
C5.7	Topics in Fluid Mechanics	16 MT
C5.9	Mathematical Mechanical Biology	16 MT
C5.11	Mathematical Geoscience	16 MT
C5.12	Mathematical Physiology	16 MT
C6.1	Numerical Linear Algebra	16 MT
C6.2	Continuous Optimisation	16 HT
C6.4	Finite Elements for PDEs	16 HT
C6.5	Theories of Deep Learning	16 MT
C7.1	Theoretical Physics	24MT/16HT
C7.4	Introduction to Quantum Information	16 HT
C7.5	General Relativity I	16 MT
C7.6	General Relativity II	16 HT
C7.7	Random Matrix Theory	16 HT
C8.1	Stochastic Differential Equations	16 MT
C8.2	Stochastic Analysis and PDEs	16 HT
C8.3	Combinatorics	16 MT
C8.4	Probabilistic Combinatorics (see page 13)	16 HT
C8.7	Optimal Control	16 HT
CO1.1	Newton's Principia	RC HT