POSTGRADUATE INSTITUTE OF SCIENCE

UNIVERSITY OF PERADENIYA

Master of Data Science Degree Programme
(SLQF Level 9)

Master of Science (M.Sc.) in Data Science Degree Programme
(SLQF Level 10)

1. INTRODUCTION

Data Science is an emerging interdisciplinary field of Statistics and Computer Science for which the foundational topics are Data Manipulation, Data Analysis with Statistics, Machine Learning, High Performance Computing, Data Communication with Information Visualization, and Data at Scale (Working with Big Data). Moreover, Data Science is an integral part of research in many fields, such as machine translation, speech recognition, robotics, search engines, digital economy in addition to business intelligence, operational intelligence, biological sciences, medical informatics, health care, social sciences and the humanities.

There is an explosive growth of data due to the rapid development of the Internet and digital technology. Further, data storage capacity and processing speed have increased dramatically and cost effectively. Thus, many industries deal with large volumes of data and this has resulted in a great demand and a good opportunity for graduates with statistical skills and competence in data base and in computer programming. Although it is of utmost importance to train personnel to undertake responsibilities related to the real world applications, the Sri Lankan education institutions have not paid due attention in the recent past in this rapidly growing area of science. There is also a global shortage of qualified graduates whose skills span these areas. Therefore, the M.Sc. Programme in Data Science has been designed to cater for the current demands for postgraduate training and research in the fields of big data, data mining and Computational Statistics.

2. OBJECTIVES OF THE PROGRAMME

The objectives of the programme are to provide graduates an adequate coverage of skills in Data Science with the focus of applications in the relevant fields and methods of presentation and interpretation of results. At the completion of the course, the candidate will competent as a data scientist in a research institute, planning institute or a government institute or as an information and data scientist in industries such as Finance, Banking, Retail, Telecommunication, Media and Insurance with complementary skills in statistics and computer science.

3. PROGRAMME ELIGIBILITY

Applicants must possess a science-based degree (e.g. Physical Science/Engineering related degree*)* with **Statistics and Computer Science** (with at least 9 credits from each subject) or an equivalent qualification acceptable to the Postgraduate Institute of Science. Depending on the courses successfully completed at the degree level and on the recommendation of the programme advisor a candidate may be exempted from some of the preliminary courses. Graduates, who have no basic knowledge in Mathematics, are expected to follow a course in fundamentals of Mathematics (None credit courses).

4. PROGRAMME FEE

Category	**Programme Fee**	
	Master of Data Science Degree Programme	**M.Sc. in Data Science Degree Programme**
Local candidates	Rs.350,000/- (1 year)	Rs.450,000/- (2 years)
Foreign candidates	Rs.700,000/- (1 year)	Rs.900,000/- (2 years)

Students registered for the Master of Data Science degree programme shall pay the Programme fee in full or in two *(1/2 at the registration and the balance at the end of the first semester)* or three *(1/3rd at the registration, another 1/3rd after 4 months from the date of registration and the balance after 8 months from the date of registration)* instalments. An additional payment of Rs. 100,000/- (or Rs. 200,000/- from foreign students) should be made at the end of the first year to continue for the M.Sc. in Data Science degree programme. Other payments including registration fee, medical fee, library subscription, examination fee and deposits (science and library) should be paid according to the procedure stipulated by the PGIS. (N.B. The Programme fees given above may be revised as per recommendation of the Board of Management of the PGIS.)

5. THE PROGRAMME STRUCTURE AND DURATION

This programme consists of three options for completion.

5.1 Masters Degree by Course Work (SLQF Level 9)

The Master of Data Science degree can be obtained by completing course work only (without conducting any research project).

Course work, comprising of theory courses, and laboratory and/or fieldwork, shall be conducted over a period of two semesters of 15 weeks each. The total duration of the degree, including examinations, shall be about 12 months. Satisfactory completion of a minimum of 30 credits of course work with a GPA of not less than 3.00 is required for the successful completion of the degree - SLQF Level 9 (Students who do not satisfy the above criteria but obtain a GPA in the range 2.75 to 2.99 for course work of 25 credits are eligible for the Postgraduate Diploma in Data Science - SLQF Level 8, and those who obtain a GPA in the range 2.75 to 2.99 for course work of 20 credits are eligible for Postgraduate Certificate - SLQF Level 7).

5.2 Masters Degree by Course Work and Research (SLQF Level 10)

In addition to Masters Degree with course work (5.1), the Masters Degree (Research) requires a research project. The duration of the entire programme shall be 24 months inclusive of 5.1.

Completion of all the requirements of 5.1 with a GPA of not less than 3.00 is a prerequisite for the Masters Degree (Research). The research project for this degree should be conducted on full-time basis, and completed during the second year. The research component is allocated 30 credits, totalling 60 credits for the entire programme. After successful completion of the research project, the student shall be eligible for the award of the M.Sc. in Data Science degree - SLQF Level 10 (Students who do not complete the research project within the stipulated time period shall be awarded the Master of Data Science degree - SLQF Level 9).

5.3 Extension of the programme for M.Phil. (SLQF Level 11) or Ph.D. (SLQF Level 12)

After conducting research for a period of six months in the M.Sc. degree (research) programme, students who have demonstrated exceptional progress may apply for upgrading the degree status to M.Phil. The student should continue the research project and any additional research work/assignments recommended by the PGIS for a total of two years (60 credits of research) to qualify for the award of the M.Phil. degree (SLQF Level 11).
During the second year of research, students who have demonstrated exceptional and continuous progress may apply for upgrading the degree status from M.Phil. to Ph.D. The student should continue the research project and any additional research work/assignments recommended by the PGIS for another year on full-time basis (additional 30 credits) to qualify for the award of the Ph.D. degree (SLQF Level 12).

Master of Data Science Degree Programme (SLQF Level 9)
Master of Science (M.Sc.) in Data Science Degree Programme (SLQF Level 10)

Programme Summary

Course Code	Course	Lecture hrs.	Practical hrs.	No. of Credits
Preliminary Courses				
SC 401	Mathematics†	30	-	-
SC 404	Theory of Statistics*	30	-	-
SC 417	Data Structures and Algorithms††	30	-	-
Semester I				
SC 502	Data Analysis & Report Writing	30	30	3
SC 503	Design and Analysis of Experiments	45	-	3
SC 504	Regression Analysis*	45	-	3
SC 506	Multivariate Methods I*	30	-	2
SC 507	Stochastic Processes and Applications	30	-	2
SC 571	Linear Models	30	-	2
SC 572	Statistics for Bioinformatics	20	20	2
SC 573	Machine Learning*	30	30	3
SC 574	Cloud Computing	30	30	3
Semester II				
SC 516	Time Series Modelling and Signal Processing	45	-	3
SC 517	Nonparametric and Categorical Data Analysis	45	-	3
SC 519	Multivariate Methods II*	30	-	2
SC 581	Statistical Natural Language Processing	30		2
SC 582	Machine Vision	30	30	3
SC 583	Statistical Computing and Simulation Techniques	30	30	3
SC 584	Decision Theory and Bayesian Inference	30	-	2
SC 585	Big Data Processing & Large-scale Machine Learning*	30	30	3
SC 586	Data Exploration and Visualization	30	30	3

SC 587	Special Topics in Data Science[**]	30		2
SC 599	Independent Study*[1]	500 notional hours		5
SC 699	Research Project*[2]	3000 notional hrs. (one year duration)		30
	Total Credits			**84**

Preliminary courses are not considered in the computation of the GPA

† only for those who have no mathematics background

†† only for those who have no computer programming background

* Compulsory Courses

*[1] Compulsory for Master of Data Science degree (SLQF Level 9)

*[2] Compulsory for M.Sc. in Data Science degree (SLQF Level 10)

[**] Special Topics will be notified to students in each year.

6. PROGRAMME CONTENTS

Course Code : SC401
Course Title : Mathematics
No. of Credits : 2
Pre-requisites : None
Compulsory/Optional : Compulsory for students who have not followed Mathematics as a subject for their bachelors degree.

Aim(s): To give students an introduction to mathematical concepts essential in data manipulation which includes calculus, matrix algebra and optimization.

Intended Learning Outcomes:
At the completion of the course, students will be able to
- evaluate definite and indefinite integrals.
- calculate the area under a curve.
- perform integrations by substitution and partial differentiation.
- evaluate multi dimensional data using matrix algebra.

Time Allocation (Hours): **Lectures** 30 hrs

Course content/Course description:
Number Systems, Inequalities, Elements of Set Theory. Coordinate Geometry: Lines, Circles and Parabolas. Calculus: Limits and Derivatives. Maxima, Minima and Inflextion points. Indefinite Integral, Definite Integral, Evaluation of area between curves, Integration by substitution, Partial differentiation. Matrix Algebra : Matrices, determinants and inverse of a matrix. Matrix approach to solution of system of equations. Rank of a matrix, eigen values, Introduction to numerical optimization.

Recommended Texts:

1. Hamming R.W. *Methods of Mathematics Applied to Calculus, Probability, and Statistics*, Dover Publications, 2004.
2. Waner S., Costenobel S., Applied Calculus, 6^{th} Edition, Cengage Learning, 2013.

Assessment	Percentage Mark
In-course	50%
End-semester	50%

**Course Code : ** SC404
**Course Title : ** Theory of Statistics
No. of Credits : 2
Pre-requisites : None
Compulsory/Optional : Compulsory

Aim(s): To introduce basic probability theory so that students can apply the theoretical knowledge in data analysis.

Intended Learning Outcomes:
At the end of the course students will be able to:

- identify the sample space and events of an experiment.
- calculate probabilities, conditional probabilities, expectation and variance of random variable.
- derive marginal densities and cumulative densities from a given probability distribution.
- calculate probabilities using Bayes' Rule.
- apply Central Limit Theorem to sampling distributions.
- carry out simple and composite hypothesis tests on mean, variance and proportion.
- estimate parameters using maximum Likelihood.

Time Allocation (Hours): **Lectures** 30 hrs

Course content/Course description:
Probability: Properties, conditional probability, independence. Discrete random variables: Probability mass functions and cumulative distributions. Some common discrete distributions. Continuous random variables: Marginal and conditional distributions, Bayes' Rule. Expectations and Central Limit Theorem. Sampling from the Normal distribution. Point and Interval estimation. Test of Hypotheses: Simple and composite hypothesis. Maximum likelihood estimation. Generalized Likelihood Ratio Tests. Tests on means and variances.

Recommended Texts:

1. Hogg R.V., McKean J., Craig A.T., *Introduction to Mathematical Statistics*, 7th Edition, Pearson, 2012.
2. Casella G., Berger R.L., *Statistical Inference*, 2nd Edition, Cengage Learning, 2008.

Assessment	**Percentage Mark**
In-course	50%
End-semester	50%

Course Code : SC417
Course Title : Data Structures and Algorithms
No. of Credits : 2
Pre-requisites : None
Compulsory/Optional : Optional

Aim(s): To provide students an understanding on data structures used in computer programming and then use them to manipulate data such as sorting, searching and pruning.

Intended Learning Outcomes:
At the end of the course students will be able to:
- reason about and evaluate the efficiency behaviour of a given algorithm
- select appropriate data structures and algorithms for a given problem
- implement the chosen data structures and algorithms.

Time Allocation (Hours): **Lectures** 30 hrs

Course content/Course description:
Data Structures: linear and nonlinear data structures. arrays, lists: linked list, ordered linked list and doubly linked list; push down stacks; queues: FIFO queue and deque. Tree structures – trees in general, binary search three (BST), root insertion to BST, splay tree, 2-3-4 trees, radix tree and red-black tree; Graphs; Implementation of depth first search, breadth first search; Analysis of algorithms: time complexity, big O notation. Sorting algorithms: bubble sort, selection sort, insertion sort, quick sort, heap sort, merge sort and external sorting methods. Hashing: hash functions and collision resolution: separate chaining, linear probing and double hashing. Classification of Algorithms by Implementation and Design Paradigm: Divide & Conquer Algorithms, Dynamic Programming, Greedy Algorithms, Recursive Algorithms, Backtracking, Alfa-Beta pruning, Branch & Bound Search;

Recommended Texts:
1. Baase S., Van Gelder A., *Computer Algorithms - Introduction to Design & Analysis*, Addison-Wesley, 2000.
2. Thomas H.C., Charles E. L & Ronald L. R, *Introduction to Algorithms*, McGraw-Hill, 2009.
3. Weiss M., *Efficient C Programming*, Prentice-Hall, 1995.

Assessment	Percentage Mark
In-course	50%
End-semester	50%

Course Code : SC502
Course Title : Data Analysis & Report Writing
No. of Credits : 3
Pre-requisites : SC404
Compulsory/Optional : Optional

Aim(s): To introduces most important toolkits for modern statistical inference (e.g R and SAS), and to teach students to handle a statistical software in data analysis and interpret the results appropriately.

Intended Learning Outcomes:
At the end of the course students will be able to:

- use a statistical software to perform
    - a descriptive data analysis
    - a univariate hypothesis test
    - a multiple linear regression analysis
    - a one way and two way analysis of variance
    - a Generalized Linear Models
- communicate and present the results of a statistical data analysis.
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Time Allocation (Hours): **Lectures** 30 hrs **Practicals** 30 hrs

Course content/Course description:
Introduction to Statistical Software. MINITAB: Data management, Descriptive statistics. ANOVA, GLM and Regression. Non parametrics. SAS : Data entry and editing. Structure of a SAS programme. Procedures used for ANOVA, GLM, Regression, Orthogonal and Non-orthogonal analysis, Categorical data analysis, and Multivariate analysis. Presentation of results.

Recommended Texts:

1. Booth W.C., Colomb G.G., Williams J.M., *A Manual for Writers of Research Papers, Theses, and Dissertations*, Seventh Edition: Chicago Style for Students and Researchers (Chicago Guides to Writing, Editing, and Publishing) , 7th edition, 2007.
2. Matloff N., *The Art of R Programming: A Tour of Statistical Software Design*, No Starch Press, 2011.

Assessment	**Percentage Mark**
In-course	50%
End-semester	50%

**Course Code : ** SC503
**Course Title : ** Design and Analysis of Experiments
**No. of Credits : ** 3
**Pre-requisites : ** SC404
**Compulsory/Optional : ** Optional

Aim(s): To introduce planning, designing and conducting experiments efficiently and effectively, and analyze the resulting data to obtain objective conclusions. Both design and statistical analysis issues are discussed.

Intended Learning Outcomes:

At the end of the course students will be able to:

- describe the principles of design.
- select an appropriate experimental design to a given problem.
- perform a covariance analysis of an experimental design.
- interpret the outcomes of an analysis of an experimental design.

Time Allocation (Hours): **Lectures** 45 hrs

Course content/Course description:

Principles of design. Completely randomized and complete Block Design. Latin Square Design and its variations. Covariance analysis. Factorial experiments, fixed and random effects model, split plot designs. Nested factorials. Incomplete block designs. Balanced and partially balanced incomplete block designs. Confounding and fractional factorials in 2^n, 3^n and p^n experiments. Asymmetric factorials. Lattice designs. Diallel experiments. Basic ideas in construction of design.

Recommended Texts:

1. Montgomery D.C., *Design & Analysis of Experiments*, 8^{th} Edition, Wiley, 2012.
2. Jobson J.D. , *Applied multivariate data analysis : Regression and Experimental Design*, Springer, 1991.

Assessment	**Percentage Mark**
In-course	50%
End-semester	50%

Course Code : SC504
Course Title : Regression Analysis
No. of Credits : 3
Pre-requisites : SC404
Compulsory/Optional : Compulsory

Aim(s): To acquaint students with Least Square methods and concept of linear and multiple regression, correlation, and its applications, To approach the material with matrices algebra, To develop the ability to build linear and nonlinear regression models.

Intended Learning Outcomes:

At the end of the course students will be able to:

- write regression model in matrix form.
- calculate least square estimates and Maximum Likelihood estimates of regression parameters.
- identify remedies for hetroscedasticity and multicollinearity.
- analyse data using multiple regression techniques.
- perform kernel smoothing.
- use unsupervised learning method to fit regression models

Time Allocation (Hours): **Lectures** 45 hrs

Course content/Course description:

Simple linear regression and correlation, lack of fit, residual plots, Extension to multiple linear regression, Matrix approach to linear regression, Linear models. Multiple linear regression, Interpretation of coefficients. Inferences in regression analysis. Sequential and partial regression sums of squares. Analysis of aptness of the model. Model selection procedures. Introduction to non-linear regression.

Introduction to regression models, matrix formulation, Gram-Schmidt theory, Regression LSEs, Regression MLEs under normality, confidence sets and LR tests, Cross sectional modeling and Hetroscedasticity, Multicollinearity, Ridge regression, weighted and generalized least squares, Multiple Regression, Logistic Regression, Non-linear and maximum Likelihood Modeling, Splines and other bases, Kernel smoothing.

Recommended Texts:

1. Kutner M.H., *Applied Statistical Models*, McGraw-Hill education, 2013.
2. Christensen R. , *Analysis of Variance, Design and Regression: Linear modelling for unbalanced data*, Chapman & Hall/CRC 2, 2015

Assessment	Percentage Mark
In-course	50%
End-semester	50%

Course Code : SC506
Course Title : Multivariate Methods I
No. of Credits : 2
Pre-requisites : SC404
Compulsory/Optional : Compulsory

Aim(s): To teach the student about multivariate visualization, multivariate normal distribution, hypothesis testing for multivariate data and statistical methods that uncover surprising but valid linkages between variables and explain and predict their measured values.

Intended Learning Outcomes:
At the end of the course students will be able to:
- list methods of visualizing multivariate data sets
- identify the usage of multivariate normal distribution
- perform statistical tests of the mean value vector of a multivariate normal distribution
- perform statistical tests of two or several populations of a multivariate normal distribution
- conduct methods and techniques for validation of multivariate normal distribution.
- use principal component and factor analysis for multivariate data sets

Time Allocation (Hours): **Lectures** 30 hrs

Course content/Course description:
Introduction to multivariate analysis. Multivariate normal distribution. Expected values. Variance - Covariance matrix. Principal component analysis (PCA). Interpretation using illustrative examples. Factor analysis. Comparison with PCA, factor loadings, rotations, Interpretation. Cluster Analysis.

Recommended Texts:

1. Johnson R. A. and Wichern D.W., *Applied Multivariate Statistical Analysis*, 6th Edition, Pearson publications, 2007.
2. Rencher A.C. , *Multivariate Statistical inference & Applications*, Wiley Interscience, 1997.

Assessment	Percentage Mark
In-course	50%
End-semester	50%

Course Code : SC507
Course Title : Stochastic Processes and Applications
No. of Credits : 2
Pre-requisites : SC404
Compulsory/Optional : Optional

Aim(s): To give an introduction to the theory of stochastic processes in with special emphasis on applications and examples**.**

Intended Learning Outcomes:
At the end of the course students will be able to:
- explain high levels of concepts from probability and describe basic stochastic processes.
- evaluate various quantities for probability distributions and random variables.
- formulate and solve problems about stochastic processes.
- develop mathematical models for a range of empirical phenomena and analyse models of queuing system on the basis of stochastic processes.

Time Allocation (Hours): **Lectures** 30 hrs

Course content/Course description:
Recurrent events, Random walks, Markov chains, Transition probabilities, Limiting distributions, Discrete branching processes, Markov processes in continuous time, Poisson processes and their applications, Birth & Death processes, Queuing theory and applications.

Recommended Texts:
1. Gallager R.G., *Stochastic Processes: Theory for Applications*, 1st Edition, Cambridge University Press, 2014.
2. Ross S.M. *, Introduction to probability models*, 11th Edition, Academic Press, 2014.

Assessment	**Percentage Mark**
In-course	50%
End-semester	50%

Course Code : SC516
Course Title : Time Series Modelling and Signal Processing
No. of Credits : 3
Pre-requisites : SC404
Compulsory/Optional : Optional

Aim(s): To provide students with the basic theory and tools for the statistical analysis and interpretation of time series.

Intended Learning Outcomes:

At the end of the course students will be able to:

- define time series data in an appropriate statistical framework.
- summarize and carry out exploratory and descriptive analysis of time series data.
- describe and conduct appropriate statistical modeling techniques for time series data.
- use R competently to model and produce point and interval forecasts and interpret the results for time series data.
- derive the statistical properties of linear time series models.
- present and communicate, both orally and in written-form, the results of statistical analyses of time series data

Time Allocation (Hours): **Lectures** 45 hrs

Course content/Course description:

Time domain methods: Introduction and examples, Stationary processes, Filtering, MA, AR, and ARMA processes, causal and invertible processes, Spectral representation of a stationary process, Prediction in frequency domain, Recursive computation of the best linear predictor and its mean squared error, Estimation and model selection, Goodness-of-fit issues, Non stationary time series, ARIMA models and extensions. ARCH/GARCH models. Frequency domain methods: basis functions, furrier transform, FFT, Financial time series modelling.

Recommended Texts:

1. Brockwell P. and Davis R. , *Time Series: Theory and Methods*, Springer publications, 2009.
2. Chatfield C., *The Analysis of Time Series, An Introduction*, Chapman & Hall, 2003.

Assessment	**Percentage Mark**
In-course	50%
End-semester	50%

Course Code : SC517
Course Title : Non parametric and Categorical data analysis
No. of Credits : 3
Pre-requisites : SC404
Compulsory/Optional : Optional

Aim(s): To introduce students the wide range of interesting nonparametric ideas in statistics. Some of those ideas are theoretical, others are computational and methodological.

Intended Learning Outcomes:
At the end of the course students will be able to:

- describe the properties of commonly used statistical distributions for modelling non-normal data
- decide whether parametric or non-parametric test is suitable for analyzing data in a certain situation as well as carrying out the test
- use the basic methods for analyzing contingency tables
- recognize and define the categorical data, recall key concepts of models for categorical data, state analysis plan and reproduce a research design.

Time Allocation (Hours): **Lectures** 45 hrs

Course content/Course description:
Non parametric tests for one sample test: sign test, sign rank test, non parametric tests for independent two sample test and paired test, Spearman Rank, Kruskal-Wallis test, types of categorical data, Chi squared test for independency, Odds ratio, relative risk calculation, ordinal and nominal logistic regression, Measures of association.

Recommended Texts:

1. Gibbons J.D., S. Chakraborti, *Nonparametric Statistical Inference*, 5th Edition, Chapman and Hall/CRC Press, 2010.
2. Sprent P., *Applied Nonparametric Statistical Methods*, 4th Edition, Chapman and Hall/CRC Press, 2007.
3. Agresti A., *Categorical Data Analysis*, 3rd Edition, Wiley, 2012.

Assessment	Percentage Mark
In-course	50%
End-semester	50%

Course Code : SC519
Course Title : Multivariate Methods II
No. of Credits : 2
Pre-requisites : SC506
Compulsory/Optional : Compulsory

Aim(s): To introduce further topics in Multivariate Analysis as an extension to SC506.

Intended Learning Outcomes:
At the end of the course students will be able to:

- identify the relevant method to reduce high dimensional data
- use methods for multiple inference
- evaluate covariance structure models

Time Allocation (Hours): **Lectures** 30 hrs

Course content/Course description:
Two-groups Discriminant analysis. Multiple-group Discriminant analysis. Multivariate analysis of variance. Canonical correlation. Covariance structure models. Multivariate Data Visulization; Multidimensional scaling, correspondence analysis, Biplots.

Recommended Texts:

1. Johnson R.A. and Wichern D.W., *Applied Multivariate Statistical Analysis*, 6^{th} Edition, Pearson publications, 2007
2. Rencher A.C., *Multivariate Statistical inference & Applications*, Wiley Interscience, 1997.

Assessment	Percentage Mark
In-course	50%
End-semester	50%

Course Code : SC571
Course Title : Linear Models
No. of Credits : 2
Pre-requisites : SC404
Compulsory/Optional : Optional

Aim(s): To provide a theoretical knowledge in understanding linear models.

Intended Learning Outcomes:
At the end of the course students will be able to:
- present different linear models in matrix form.
- derive Best Linear Unbiased Estimators (BLUEs) for given models.
- analyse random and mixed effect models.

Time Allocation (Hours): **Lectures** 30 hrs

Course content/Course description:
Review of linear algebra, Random vectors and matrices, quadratic forms and distribution theory, The full rank linear model, The non-full rank linear model (eg: ANOVA, ANCOVA), estimable functions, best Linear Unbiased Estimators (BLUEs), Multiway classifications, random and mixed effect model, variance components.

Recommended Texts:
1. Searle S.R., *Linear Models*, 1st Edition, Wiley Interscience, 2012.
2. Graybill F.A., *Theory and Application of the Linear Models*, 1st Edition, Prindle Weber & Schmidt, 1976.

Assessment	Percentage Mark
In-course	50%
End-semester	50%

**Course Code : ** SC572
**Course Title : ** Statistics for Bioinformatics
**No. of Credits : ** 2
**Pre-requisites : ** SC404
**Compulsory/Optional : ** Optional

Aim(s): To introduce statistical methods commonly used to solve bioinformatics problems. Relevant concepts from probability, statistical inference will be introduced and illustrated by examples from bioinformatics applications.

Intended Learning Outcomes:
At the end of the course students will be able to:
- summarize gene expression technology and its purpose
- visualize gene expression data
- apply statistical methods to identify the most important genes for differentiation
- perform DNA/Protein sequencing and analysis
- estimate the allele and genotype frequencies in a population

Time Allocation (Hours): **Lectures** 20 hrs **Practicals** 20 hrs

Course content/Course description:
Introduction to Cell biology and genetics: Cell, DNA and chromosomes, functions of the cell and DNA. Gene Expression analysis: Pre-processing, Visualization, Inference. Sequence Analysis and alignment: DNA/Protein sequence analysis, aligning sequences, Markov chains. Genetic frequencies: ML estimation, exact test.

Recommended Texts:
1. Ewens W.J., Grant G.R., *Statistical Methods in Bioinformatics: An Introduction (Statistics for Biology and Health),* Springer, 2001.
2. Lu H.H., Schölkopf B., Zhao H., *Handbook of Statistical Bioinformatics (Springer Handbooks of Computational Statistics),* 2011.
3. Deonier R.C., Tavaré S., Waterman M., *Computational Genome Analysis: An Introduction*, Springer, 2007.

Assessment	**Percentage Mark**
In-course	50%
End-semester	50%

Course Code : SC573
Course Title : Machine Learning
No. of Credits : 3
Pre-requisites : SC504
Compulsory/Optional : Compulsory

Aim(s): To introduce basic machine learning and optimization techniques essential in big data handling.

Intended Learning Outcomes:

At the end of the course students will be able to:

- list some of the main machine learning and advanced optimisation techniques used in artificial intelligence;
- analyse the results of applying a range of machine learning and advanced optimisation techniques, and be able to compare and contrast these results on a range of criteria (and write the necessary software to undertake this);
- apply machine learning and advanced optimization techniques to significant and real-world problem domains.

Time Allocation (Hours): **Lectures** 30 hrs **Practicals** 30 hrs

Course content/Course description:

Introduction and basic concepts: Statistical model, loss function, empirical risk minimization, etc., Numerical Optimization: Gradient Descent, Newton's Method, IRLS, Coordinate Descent, etc. ,Regression and Classification, Practical model building:
Feature pre-processing, Bias variance trade-off, Feature selection and regularization (L1, L2), Cross validation/Hyper-parameter tuning, Model diagnostics, Performance metrics: RMSE, AUC, SE, SP, Fm, etc., Non-linear models: SVMs, Decision Trees, Artificial Neural Networks (Back propagation), Ensemble models: Bagging/Bootstrapping-random Forest, Boosting: Adaboost, GBMs, etc. ,Performance metrics: RMSE, AUC, SE, SP, Fm, etc.

Recommended Texts:

1. James G., Witten D., Hastie T., Tibshirani R., *An Introduction to Statistical Learning: with Applications in R*, Springer Texts in Statistics, 2013.
2. Hastie T., Tibshirani R., Friedman J., *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, 2nd Edition, Springer Series in Statistics, 2009.
3. Lantz B., *Machine Learning with R*, 2nd Edition, Packt Publishing, 2015.

Assessment	**Percentage Mark**
In-course	50%
End-semester	50%

Course Code : SC574
Course Title : Cloud Computing
No. of Credits : 3
Pre-requisites : None
Compulsory/Optional : Optional

Aim(s): To introduce cloud computing in detail and introduces the security concerns associated with cloud computing.

Intended Learning Outcomes:
At the end of the course students will be able to:

- identify Parallel and Distributed Systems Context
- demonstrate Cloud Virtualization, Abstractions and Enabling Technologies
- evaluate performance, scalability and consistency on Clouds
- evaluate security aspects of Clouds and Cloud Computing

Time Allocation (Hours): **Lectures** 30 hrs **Practicals** 30 hrs

Course content/Course description:
Introduction to Cloud Computing, Cloud computing technologies and types, matching cloud providers to user needs, parallel computing and distributed systems, Challengers and opportunities of big data, Large scale distributed file systems, Large scale distributed access structures, NoSQL databases, MapReduce and Hadoop, Running Hadoop in the cloud using Amazon EMR, Developing MapReduce programmes, Link analysis in Cloud, Data management in Cloud, Information retrieval in the Cloud, Beyond MapReduce (Limitations of MapReduce, extensions to MapReduce, Alternatives to MapReduce/Hadoop, Apache Spark), Introduction to Security of Cloud Computing.

Recommended Texts:

1. Marinescu D., *Cloud Computing: Theory and Practice*, Morgan Kaufmann, 2013.
2. Rosenberg J., Mateos A., *The Cloud at Your Service*, Manning, 2010.
3. Lin J., Dyer C., *Data-Intensive Text Processing with MapReduce*, Morgan and Claypool, 2010.
4. Rajaraman A., Ullman J., *Mining of Massive Datasets*, Cambridge University Press, 2011.

Assessment	Percentage Mark
In-course	50%
End-semester	50%

Course Code : SC581
Course Title : Statistical Natural Language Processing
No. of Credits : 2
Pre-requisites : SC573
Compulsory/Optional : Optional

Aim(s): To provide students with a theoretical and practical grounding in the most important topics in the field of Natural Language Processing (NLP).

Intended Learning Outcomes:

At the end of the course students will be able to:

- use concepts in text mining and statistical natural language processing (NLP.
- employ tools and methods used in text mining and NLP.
- implement basic systems to perform the following NLP tasks and test these systems on datasets used by the NLP research community.

Time Allocation (Hours): **Lectures** 30 hrs

Course content/Course description:

Introduction, Mathematical Foundations, Linguistic Essentials, Corpus-Based work, Collocations, *n-gram* models over sparse data, Word sense disambiguation, Lexical Acquisition, Markov Models, Probabilistic Context Free Grammers, Machine Translation, Document Classification and Clustering, Tagging, Syntactic Parsing, Information Extraction, Semantic Parsing, Probabilistic Parsing.

Recommended Texts:

1. Jurafsky D., Martin J.H. , *Speech and Language Processing: An Introduction to Natural Language Processing*, Computational Linguistics and Speech Recognition. 2nd Edition. Prentice Hall, 2008.
2. Manning C., Schuetze H., *Foundations of Statistical Natural Language Processing*, The MIT Press, 1999.

Assessment	**Percentage Mark**
In-course	50%
End-semester	50%

Course Code **:** SC582
Course Title **:** Machine Vision
No. of Credits **:** 3
Pre-requisites **:** SC573
Compulsory/Optional : Optional

Aim(s): To addresses algorithms for automated computer vision. It focuses on building statistical/mathematical models of images and objects and using these to perform inference.

Intended Learning Outcomes:
At the end of the course students will be able to:
- apply a series of probabilistic models of images and objects in machine vision systems.
- use these models to automatically find, segment and track objects in scenes, perform face recognition and build three-dimensional models from images.
- identify principles behind face recognition, segmentation, image parsing, super-resolution, object recognition, tracking and 3D model building.

Time Allocation (Hours): **Lectures** 30 hrs **Practicals** 30 hours

Course content/Course description:
Two-dimensional visual geometry: 2d transformation family. The homography. Estimating 2d transformations. Image panoramas. Three dimensional image geometry: The projective camera. Camera calibration. Recovering pose to a plane. More than one camera: The fundamental and essential matrices. Sparse stereo methods. Rectification. Building 3D models. Shape from silhouette. Vision at a single pixel: background subtraction and color segmentations problems. Parametric, non-parametric and semi-parametric techniques. Fitting models with hidden variables. Connecting pixels: Dynamic programming for stereo vision. Markov random fields. MCMC methods. Graph cuts. Texture: Texture synthesis, super-resolution and denoising, image inpainting. The epitome of an image. Dense Object Recognition: Modelling covariance of pixel regions. Factor analysis and principle components analysis. Sparse Object Recognition: Bag of words, latent dirilecht allocation, probabilistic latent semantic analysis. Face Recognition: Probabilistic approaches to identity recognition. Face recognition in disparate viewing conditions. Shape Analysis: Point distribution models, active shape models, active appearance models. Tracking: The Kalman filter, the Condensation algorithm.

Recommended Texts:
1. Prince S.J.D., *Computer Vision: Models, Learning, and Inference*, Cambridge University Press,2012.
2. Davies E. R., *Computer and Machine Vision, Theory, Algorithms, Practicalities*, Academic Press, 2012.

Assessment	Percentage Mark
In-course	50%
End-semester	50%

Course Code : SC583
Course Title : Statistical computing and Simulation Techniques
No. of Credits : 3
Pre-requisites : SC404
Compulsory/Optional : Optional

Aim(s): To introduces Monte Carlo methods, collectively one of the most important toolkits for modern statistical inference.

Intended Learning Outcomes:
At the end of the course students will be able to:

- generate random numbers using different algorithms.
- generate random variates of a given probability distribution.
- approximate functions and probabilities using different computational methods.
- simulate random events in R using MCMC, Metropolis-Hastings Algorithm etc.
- conduct bootstrap sampling and Gibbs sampling.
- apply different variance reduction techniques.
- use Monte Carlo methods in statistical programming and simulations.

Time Allocation (Hours): **Lectures** 30 hrs **Practicals** 30 hours

Course content/Course description:
Introduction to R, generating random variables, Methods of approximating functions and probabilities, computational methods in linear algebra, bootstrap method, Markov Chain Monte Carlo method (MCMC), Gibbs sampling, Metropolis-Hastings Algorithm, variance reduction methods, EM and related algorithms. Practical simulation models using case studies.

Recommended Texts:

1. Ross S.M., *Simulation (Statistical Modeling and Decision Sciences)*, 4th Edition.APress, 2006.
2. Law A.M., Kelton W.D., *Simulation Model and Analysis*, 3rd Edition, McGraw-Hill, 1999.
3. Borshchev A., *The Big Book of Simulation Modeling, Multimethod Modeling with AnyLogic*, Anylogic North America, 2013.

Assessment	**Percentage Mark**
In-course	50%
End-semester	50%

Course Code : SC584
Course Title : Decision Theory and Bayesian Inference
No. of Credits : 2
Pre-requisites : SC404
Compulsory/Optional : Optional

Aim(s): To familiarize students in fundamental concepts of the statistical decision theory and Bayesian inference.

Intended Learning Outcomes:

At the end of the course students will be able to:

- formulate a decision theoretic approach to the problem
- evaluate a utility function
- propose a conjugate family of prior distributions
- evaluate Bayes and posterior risks and find the optimal solution
- apply empirical and hierarchical Bayes approaches.

Time Allocation (Hours): **Lectures** 30 hrs

Course content/Course description:

Introduction and philosophy, Loss function and risk, Utility and Risk, Prior and posterior, Conjugate families, Generalized Bayes rules, Bayesian estimation, Bayesian hypothesis testing, Prediction, Empirical Bayes rules, Hierarchical Bayes analysis, Bayesian robustness, Admissibility of Bayes rules, Bayesian calculation, Game theory and the minimax theorem, Naive Bayes Model, Bayesian Networks.

Recommended Texts:

1. Berger J.O., *Statistical Decision Theory and Bayesian Analysis*, 2nd edition, Springer-Verlag, 2010.
2. Liese F. , Miescke K. J., *Statistical Decision Theory: Estimation, Testing, and Selection* , Springer Series in Statistics, 2008.

Assessment	Percentage Mark
In-course	50%
End-semester	50%

Course Code : SC585
Course Title : Big Data Processing and Large-scale Machine Learning
No. of Credits : 3
Pre-requisites : SC573, SC574
Compulsory/Optional : Compulsory

Aim(s): To familiarize students in applying large scale machine learning techniques for big data.

Intended Learning Outcomes:
At the end of the course students will be able to:

- apply distributed parallel computing techniques to handle big data.
- apply distributed machine learning and optimization methods to big data.
- evaluate large scale linear and non linear models.

Time Allocation (Hours): **Lectures** 30 hrs **Practicals** 30 hours

Course content/Course description:
Introduction, Modern distributed parallel computing: MapReduce/Hadoop, Spark, Distributed Machine Learning: Distributed Gradient Descent and other optimization methods, Hadoop Mahaut, Spark MLLib, Single-machine large scale Machine Learning: Stochastic Gradient Descent and other advancements, Large scale linear models with Vowpal Wabbit, Liblinear, Large scale non linear models with XGboost, Large-scale applied Data Science/Machine Learning: Computational advertising (Exploration Vs. Exploitation, Contextual Bandit algorithms) , Recommender systems (Matrix Factorization/SVD, Alternating least-squares), Text processing.

Recommended Texts:

1. Sakr S., Gaber M., *Large scale and big data: Processing and Management*, Auerbach Publications, 2014.
2. Guller M., *Big Data Analytics with Spark: A Practitioner's Guide to Using Spark for Large Scale Data Analysis*, Academic press, 1st Edition, 2015.

Assessment	**Percentage Mark**
In-course	50%
End-semester	50%

Course Code : SC586
Course Title : Data Exploration and visualization
No. of Credits : 3
Pre-requisites : SC404
Compulsory/Optional : Optional

Aim(s): To introduce statistical and visualisation techniques for the exploratory analysis of data.

Intended Learning Outcomes:

At the end of the course students will be able to:

- perform exploratory data analysis using a range of visualisation tools;
- describe the role of data exploration and visualisation in data science and its limitations;
- critically evaluate and interpret a data visualisation;
- distinguish standard visualisations for qualitative, quantitative, temporal and spatial data;
- select an appropriate data exploration and visualisation;
- implement interactive data visualisations using python, R and other tools.

Time Allocation (Hours): **Lectures** 30 hrs **Practicals** 30 hours

Course content/Course description:

Introduction to Business Intelligence (BI) and Business Analytics (BA), Data exploration and visualization in BI/BA context, Know about data: Data sources, Data structures, Merging data sets, Samples and sampling bias, Data dictionaries and Meta-data; Overview of exploring: filtering, sorting, summary statistics, etc; Detecting and dealing with exceptions: missing values, outliers and extreme values; Transforming variables and creating new derived variables; software tools for data exploration; Using visualization for Directed/Exploratory navigation; Basic charts and best practices: Bar chart, line-graph, box-plot, scatter plot, etc; Specialized and advanced charts: heat-map, tree map, map chart, etc; interactive visualization tools; introduction to dimension reduction.

Recommended Texts:

1. Tukey J. W., *Exploratory data analysis*, 1^{st} Edition, Pearson, 1977.
2. Mosteller F.M., Tuckey J.W., *Understanding Robust and Exploratory Data Analysis*, 1st Edition, Wiley-Interscience, 2000.

Assessment	Percentage Mark
In-course	50%
End-semester	50%

Course Code : SC587
Course Title : Special Topics in Data Science
No. of Credits : 2
Pre-requisites : None
Compulsory/Optional : Optional

Aim(s): To introduce emerging concepts, tools and technologies to students.

Intended Learning Outcomes:
At the end of the course students will be able to:
- describe specific concept/tool/technology.
- describe the principles of the concept/tool/technology discussed.
- apply the specific concept/too/technology in practical applications.

Time Allocation (Hours): **Lectures** 30 hrs

Course content/Course description:
The special topics will be different in different years and will be based on the latest developments in Data Science field.

Assessment	Percentage Mark
In-course	50%
End-semester	50%

**Course Code : ** SC599
**Course Title : ** Independent Study
**No. of Credits : ** 5
**Pre-requisites : ** SC504, SC506, SC573, SC574
**Compulsory/Optional : ** Compulsory

Aim(s): To prepare students through major steps of a case study including topic selection related to big data and carryout literature survey, model building, analysis and presentation of findings.

Intended Learning Outcomes:

At the end of the course students will be able to:

- conduct a literature review for a big data related problem
- clearly define the objective and methodology of a research problem
- conduct a mini research project or a case study in statistics related problem
- prepare presentations on the analysis outcomes

Time Allocation (Hours): 500 notional hours

Course content/Course description:

Students will study the information on selected research papers and present them in the form of seminars. By involving in an industry related study students will write research proposals and present it.

Recommended Texts:

1. Backwell, J. and Martin, J., *A Scientific approach to Scientific writing*, Springer, 2011.
2. Postgraduate Institute of Science (2016) Guidelines for writing M.Sc. Project Report/M.Phil. Thesis/ PhD Thesis.

Assessment	Percentage Mark
In-course	50%
End-semester	50%

Course Code : SC699
Course Title : Research Project
No. of Credits : 30
Pre-requisites : GPA of 3.00 at SLQF
Compulsory/Optional : Optional

Aim(s): To prepare the student to conduct a research independently by training them to plan, design and conduct a scientific research, to gather reliable scientific data, analyse, and interpret, and to develop skills in scientific writing.

Intended Learning Outcomes:
At the end of the course students will be able to:
- apply the scientific method.
- design a research project.
- complete a research project.
- follow ethical issues in scientific research
- identify the patenting process in research
- prepare presentations at national/international conferences.
- produce a thesis conforming to the requirements of the PGIS.
- write manuscripts for publication in refereed journals.

Time Allocation (Hours): 3000 notional hrs. (one year duration, full-time)

Course content/Course description:
The students will conduct sufficient amount of work on a chosen research topic under the guidance provided by an assigned supervisor/s, make a presentation of research findings at a national/international conference, and produce a thesis.

Assessment	Percentage Mark
In-course	50%
End-semester	50%

7. PROGRAMME EVALUATION

Evaluation of Course work

Based on the scheme given below, the overall performance of a student in a given course shall be evaluated by the respective instructor(s) and a grade shall be assigned.

Evaluation Scheme

- For all courses a minimum of 80% attendance is expected.
- The evaluation of each course shall be based on within course and end of course examinations, and assignments. The weightage of marks given below can generally be used as a guideline in the computation of the final grade.

End of course examination	50 - 60%
Continuous assessments (mid-semester examination, assignments, etc.)	40 - 50%
- Courses with laboratory and/or fieldwork shall be evaluated, where applicable, on a continuous assessment basis.
- The minimum grade a student should achieve to pass a course is C.
- Students will be informed of the evaluation scheme by the instructor at the beginning of a given course.

Grade Points and Grade Point Average (GPA)

The Grade Point Average (GPA) will be computed using the grades earned for core courses and optional courses, taken for credit. Preliminary courses, industrial training, research project and seminar will be evaluated on a pass/fail basis.

On completion of the end of course examination, the instructor(s) is/are required to hand over the grades of a given course to the programme coordinator who will assign the Grade Points using the following table:

Grade	Grade Point
A+	4.0
A	4.0
A^-	3.7
B^+	3.3
B	3.0
B^-	2.7
C^+	2.3
C	2.0
F	0.0

The Grade Point Average (GPA) will be computed using the formula:

$$\text{GPA} = \frac{\sum c_i g_i}{\sum c_i}$$ where c_i is the number for the i^{th} course, and

g_i is the grade point for the i^{th} course

Make-up Examinations

'Make-up' examinations may be given only to students who fail to sit a particular examination due to medical or other valid reasons acceptable to the PGIS.

Repeat Courses

If a student fails a course or wishes to improve his/her previous grade in a course, he/she shall repeat the course and course examinations at the next available opportunity. However, he/she may be exempted from repeating the course, and repeat only the course examinations if recommended by the teacher-in-charge or M.Sc. Programme Coordinator. The student may repeat the same course or a substituted (new) optional course in place of the original course. A student is allowed to repeat five credits of coursework free-of-charge. The maximum number of credits a candidate is allowed to repeat is fifteen. The maximum grade, a candidate could obtain at a repeat attempt is a B and he/she is allowed to repeat a given course only on two subsequent occasions.

Evaluation of Research Project

Research project will be evaluated on the basis of a written report (M.Sc. project report) and oral presentation (see Section 6.0 of the PGIS Handbook for the format of the project report).

8. TEACHING PANEL

	Name and Affiliation	Field of specialization
1.	Dr. H.T.K. Abeysundara, Dept. Statistics and Computer Sc., Faculty of Science, Univ. of Peradeniya, *B.Sc. (Perad.), M.Sc., Ph.D. (Texas Tech)*	*Statistics (Asymptotic Theory and Functional data analysis)*
2.	Dr. S.P. Abeysundara, Dept. Statistics and Computer Sc., Faculty of Science, Univ. of Peradeniya, *B.Sc. (Perad.), M.Sc., Ph.D. (Texas Tech)*	*Statistics(Nonlinear modelling & Optimization)*
3.	Dr. H.R.O.E. Dayaratna, Dept. Statistics and Computer Sc., Faculty of Science, Univ. of Peradeniya, *B.Sc. (Perad.), Ph.D. (Tokiyo)*	*Computer Networking*
4.	Prof. W. B. Daundasekara, Dept. of Mathematics, Faculty of Science, Univ. of Peradeniya, *B.Sc. (Perad.), M.A., Ph.D. (Alabama)*	*Mathematics*
5.	Dr. P.L. Gamage, Department of Statistics, Faculty of Science, Univ. of Colombo, *B.Sc. (Cmb.), M.Sc., Ph.D. (Texas Tech)*	*Asymptotic Theory*
6.	Dr. D.S.K. Karunasinghe, Dept. of Eng. Mathematics, Faculty of Engineering, Univ. of Peradeniya,*B.Sc.Eng (Perad.), Ph.D. (NUS)*	*Mathematics & Statistics*
7.	Prof. S.R. Kodituwakku, Dept. of Statistics & Computer Science, Faculty of Science, Univ. of *Peradeniya, B.Sc. (Perad.), M.Sc. (AIT), Ph.D. (RMIT)*	*Database Systems and Distributed Systems*
8.	Dr. M.J. Kumara, Dept. Statistics and Computer Sc., Faculty of Science, Univ. of Peradeniya, *B.Sc. (Perad.), Ph.D. (North Texas)*	*Medical Image/Video Processing, Artificial Intelligence*
9.	Dr. L.S. Nawarathna, Dept. Statistics and Computer Sc., Faculty of Science, Univ. of Peradeniya *B.Sc. (Perad.), Ph.D. (University of Texas)*	*Method comparison studies, Biostatistics*
10.	Dr. U.H.G.R.D. Nawarathna, Dept. Statistics and Computer Sc., Faculty of Science, Univ. of Peradeniya, B.Sc. (*Perad.), Ph.D. (North Texas)*	*Medical Image processing, Machine Learning*
11.	Dr. R. Palamakumbura, Dept. of Eng. Mathematics, Faculty of Engineering, Univ. of Peradeniya, *B.Sc. (Perad.), M.Sc., Ph.D. (Texas Tech)*	*Pattern generation in coupled mechanical systems, Statistics*

	Name and Affiliation	Field of specialization
12.	Prof. A.A.I. Perera, Dept. of Mathematics, Faculty of Science, Univ. of Peradeniya, *B.Sc. (Perad.), M.Sc. (Oslo), Ph.D. (RMIT)*	*Mathematics*
13.	Dr. A.A.S. Perera, Dept. of Mathematics, Faculty of Science, Univ. of Peradeniya, *B.Sc. (Perad.), Ph.D. (SUNY/Albany)*	*Mathematics*
14.	Dr. K. Perera, Dept. of Eng. Mathematics, Faculty of Engineering, Univ. of Peradeniya, *B.Sc. (J'pura), Ph.D. (SUNY/Albany)*	*Statistics*
15.	Dr. U.A.J. Pinidiyaarachchci, Dept. Statistics and Computer Science, Univ. of Peradeniya, B.Sc.(*Perad.), Ph.D.(Uppsala)*	*Computer Vision*
16.	Dr. P.M.A.R. Saranga, Dept. Statistics and Computer Sc., Faculty of Science, Univ. of Peradeniya, *B.Sc. (Cmb.), Ph.D. (Leipzig)*	*Spatial Statistics*
17.	Dr. R. Siyambalapitiya, Dept. Statistics and Computer Science, Faculty of Science, Univ. Peradeniya, B.Sc. (*Perad.*), Ph.D. (Perad.)	*Operating Systems*
18.	Dr. C. Walgampaya, Dept. of Eng. Mathematics, Faculty of Engineering, Univ. of Peradeniya, *B.Sc.Eng (Perad.), Ph.D. (Louisville)*	*Click fraud detection, Automatic web robots and Agents*
19.	Prof. P. Wijekoon, Dept. Statistics and Computer Sc., Faculty of Science, Univ. of Peradeniya, *B.Sc. (Kel.), Ph.D. (Dortmund)*	*Statistics* (*Linear Models and Multivariate Statistics)*
20.	Dr. R.D. Yapa, Dept. Statistics and Computer Sc., Faculty of Science, Univ. of Peradeniya, *B.Sc.(J'pura), M.Sc. (Cmb.), Ph.D.(Hiroshima)*	*Image processing, Data Mining and Bioinformatics*

PROGRAMME COORDINATORS

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