Indian Institute of Space Science and Technology

Thiruvananthapuram

M.Tech. Machine Learning and Computing Curriculum & Syllabus

(Effective from 2018 Admission)

Department of Mathematics

Program Educational Objectives (PEO)

1. Provide students with comprehensive theoretical and practical knowledge in machine learning and computing, enabling them to contribute effectively to research and innovation in ML & C, including a deep understanding of algorithms, data structures, and computational methods.
2. Foster interdisciplinary learning by integrating concepts from mathematics, computer science, statistics, and other domain-specific areas, empowering students to address real-world challenges holistically,through projects,case studies and model selection.
3. Prepare students for careers in the industry by offering hands-on experience with customised tools, techniques, and methodologies used in machine learning and computing, ensuring their readiness to meet the demands of the industry.
4. Educate students about the ethical implications of machine learning and computing, emphasising fairness and responsible use of artificial intelligence to instil ethical awareness in their professional practices.

Program Outcomes

1. Graduates will acquire advanced skills in designing, implementing, and evaluating machine learning algorithms, equipping them to tackle complex problems across diverse domains by translating theoretical knowledge into practical applications.
2. Graduates will receive training to contribute to machine learning and computing knowledge creation, demonstrating critical thinking skills in data analysis, result interpretation, and decision-making using machine learning models.
3. They will possess a comprehensive interdisciplinary understanding of theory, techniques, and tools in machine learning and computing, to extract valuable information from data to take decisions accordingly.
4. Overall, the programme's outcome is a set of ethically trained ML graduates who can pursue careers in research, academia, industry, or entrepreneurship in the rapidly evolving field of machine learning and computing.

SEMESTER I

CODE	TITLE	L	T	P	C
MA611	Optimization Techniques	3	0	0	3
MA613	Data Mining	3	0	0	3
MA617	Numerical Linear Algebra	3	0	0	3
MA618	Foundations of Machine Learning	3	0	0	3
MA632	Data Modeling Lab I	0	0	6	2
MA633	Data Mining Lab	0	0	3	1
MA634	Foundations of Machine Learning Lab	0	0	3	1
E01	Elective I	3	0	0	3
	Total	**15**	**0**	**12**	**19**

SEMESTER II

CODE	TITLE	L	T	P	C
MA624	Advanced Machine Learning	3	0	0	3
MA625	Statistical Models and Analysis	3	0	0	3
E02	Elective II	3	0	0	3
E03	Elective III	3	0	0	3
E04	Elective IV	3	0	0	3
MA642	Data Modeling Lab II	0	0	6	2
MA643	Statistical Modeling Lab	0	0	3	1
MA644	Advanced Machine Learning Lab	0	0	3	1
	Total	**15**	**0**	**12**	**19**

SEMESTER III

CODE	TITLE	L	T	P	C
MA851	Seminar	0	0	0	1
MA852	Project Work – Phase I	0	0	0	14
	Total	**0**	**0**	**0**	**15**

SEMESTER IV

CODE	TITLE	L	T	P	C
MA853	Project Work – Phase II	0	0	0	17

LIST OF ELECTIVES FOR SEMESTER I

CODE	TITLE
MA869	Discrete Mathematics and Graph Theory
	Introduction to Internet of Things *
	Introduction to Parallel Programming *

*** Online courses from SWAYAM**

LIST OF ELECTIVES FOR SEMESTER II

CODE	TITLE
MA871	Advanced Kernel Methods
MA872	Advanced Optimization
MA873	Graphical and Deep Learning Models
MA867	Reinforcement Learning
MA874	Theory of Algorithms
MA875	Topological Data Analysis
	Cloud Computing *

*** Online courses from SWAYAM**

SEMESTER–WISE CREDITS

Semester	I	II	III	IV	Total
Credits	19	19	15	17	70

SEMESTER I

MA611	Optimization Techniques	3	0	0	3

Optimization: need for unconstrained methods in solving constrained problems, necessary conditions of unconstrained optimization, structure methods, quadratic models, methods of line search, steepest descent method; quasi-Newton methods: DFP, BFGS, conjugate-direction methods: methods for sums of squares and nonlinear equations; linear programming: simplex methods, duality in linear programming, transportation problem; nonlinear programming: Lagrange multiplier, KKT conditions, convex programing.

References:

1. Chong, E. K. and Zak, S. H., An Introduction to Optimization, 2nd Ed., Wiley India (2001).
2. Luenberger, D. G. and Ye, Y., Linear and Nonlinear Programming, 3rd Ed., Springer (2008).
3. Kambo, N. S., Mathematical Programming Techniques, East-West Press (1997).

Course Outcomes (COs):

CO1: Modelling of optimization problem mathematically

CO2: Impart knowledge on theory of optimization

CO3: Familiarize with algorithms to to solve optimization problems

CO4: Train to write programming codes for some real time optimization problems

MA613	Data Mining	3	0	0	3

Introduction to data mining concepts; linear methods for regression; classification methods: k- nearest neighbour classifiers, decision tree, logistic regression, naive Bayes, Gaussian discriminant analysis; model evaluation & selection; unsupervised learning: association rules; apriori algorithm, FP tree, cluster analysis, self organizing maps, google page ranking; dimensionality reduction methods: supervised feature selection, principal component analysis; ensemble learning: bagging, boosting, AdaBoost; outlier mining; imbalance problem; multi class classification; evolutionary computation; introduction to semi supervised learning, transfer learning, active learning, data warehousing.

References:

1. Bishop, C. M., Pattern Recognition and Machine Learning, Springer (2006).
2. Hastie, T., Tibshirani, R., and Friedman, J., The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Springer (2002).
3. Han, J., Kamber, M., and Pei, J., Data Mining: Concepts and Techniques, 3rd ed., Morgan Kaufmann (2012).
4. Mitchell, T. M., Machine Learning, McGraw-Hill (1997).

Course Outcomes (COs):

CO1: Develop a solid understanding of the fundamental concepts and principles of both machine learning and data mining.

CO2: Explore how machine learning and data mining contribute to knowledge discovery.

CO3: Cultivate critical thinking skills by analyzing and interpreting the results of machine learning and data mining algorithms in various contexts.

MA617	**Numerical Linear Algebra**	**3**	**0**	**0**	**3**

Introduction to fundamental linear algebra problems and their importance, computational difficulties using theoretical linear algebra techniques, review of core linear algebra concepts; introduction to matrix calculus; floating point representation; conditioning of problems and stability of algorithms; singular value decomposition and regularization theory.

References:

1. Datta, B. N., Numerical Linear Algebra and Applications, 2nd Ed., Siam (2010).
2. Demmel, J. W., Applied Numerical Linear Algebra, Siam (1997).
3. Lu, S. and Pereversev, S., Regularization Theory for Ill-posed Problems: Selected Topics'
4. Walter de Gruyter GmbH, Berlin/Boston, Inverse and Ill-Posed Problems Series 58.

Course Outcomes (COs) :

CO1: Learn the basic matrix factorization methods for solving systems of linear equations and linear least squares problems.

CO2: Understanding basic computer arithmetic and the concepts of conditioning and stability of a numerical method.

CO3: Study the basic numerical methods for computing eigenvalues.

CO4: Learn the basic iterative methods for solving systems of linear equations.

MA618	Foundations of Machine Learning	3	0	0	3

Machine learning basics: capacity, overfitting and underfitting, hyperparameters and validation sets, bias & variance; PAC model; Rademacher complexity; growth function; VC-dimension; fundamental concepts of artificial neural networks; single layer perceptron classifier; multi-layer feed forward networks; single layer feed-back networks; associative memories; introductory concepts of reinforcement learning, Markhov decision process.

References:

1. Mohri, M., Rostamizadedh, A., and Talwalkar, A., Foundations of Machine Learning, TheMIT Press (2012).
2. Jordon, M. I. and Mitchell, T. M., Machine Learning: Trends, perspectives, and prospects, Vol.349, Issue 6245, pp. 255-260, Science 2015.
3. Shawe-Taylor, J. and Cristianini, N., Kernel Methods for Pattern Analysis, Cambridge Univ. Press (2004).
4. Haykin, S., Neural Networks: A Comprehensive Foundation, 2nd ed., Prentice Hall (1998).
5. Hassoun, M. H., Fundamentals of Artificial Neural Networks, PHI Learning (2010).
6. Ripley, B. D., Pattern Recognition and Neural Networks, Cambridge Univ. Press (2008).
7. Sutton R. S. and Barto, A. G., Reinforcement Learning: An Introduction, The MIT Press (2017).

Course Outcomes (COs):

CO1: Ensure students grasp fundamental concepts in machine learning, including neural networks, ensemble learning, overfitting, underfitting, bias-variance tradeoff, and reinforcement learning.

CO2: Enable students to apply machine learning techniques practically.

CO3: Equip students with the ability to evaluate and interpret the performance of machine learning models, emphasizing techniques for assessing generalization capabilities and managing bias-variance trade off .

E01	Elective I	3	0	0	3

♦ **Refer list of Electives**

MA632	**Data Modeling Lab I**	**0**	**0**	**6**	**2**

Programming with Python: Introduction to Python, data types, file operations, object oriented programming.Programming with R: Introduction to R, string operations, data visualization.

Course Outcomes (COs):

CO1: Develop proficiency in Python programming, with a focus on data modeling tasks.

CO2: Acquire skills in GPU programming, enabling efficient parallel processing for machine learning tasks.

CO3: Enhance understanding of fundamental data modeling concepts and techniques through hands-on Python programming exercises.

MA633	**Data Mining Lab**	**0**	**0**	**3**	**1**

Course Outcomes (COs):

CO1:.The Data Mining Lab aims to equip students with the practical skills and confidence needed to apply data mining and machine learning techniques effectively.

CO2: Through hands-on experience and exposure to real-world datasets, students will develop a strong foundation for future applications in the field.

CO3:Enhance students ability to communicate complex technical concepts and findings effectively to both technical and non-technical audiences, promoting interdisciplinary collaboration and knowledge dissemination.

MA634	**Foundations of Machine Learning Lab**	**0**	**0**	**3**	**1**

Course Outcomes (COs):

During the Lab students undertakes various problems for classification, approximation and prediction from a data set. As an outcome of this lab, students will be able to decide what type of Neural Network Algorithm is required for training a give set of data and also they will be able to choose suitable learning rules for training data set.

SEMESTER II

MA624	Advanced Machine Learning	3	0	0	3

Kernel Methods: reproducing kernel Hilbert space concepts, kernel algorithms, multiple kernels, graph kernels; multitasking, deep learning architectures; spectral clustering ; model based clustering, independent component analysis; sequential data: Hidden Markhov models; factor analysis; graphical models; reinforcement learning; Gaussian processes; motiff discovery; graph-based semisupervised learning; natural language processing algorithms.

References:

1. Bishop, C. M., Pattern Recognition and Machine Learning, Springer (2006).
2. Hastie, T., Tibshirani, R., and Friedman, J., The Elements of Statistical Learning: DataMining, Inference, and Prediction, Springer (2002).
3. Cristianini, N. and Shawe-Taylor, J., An Introduction to Support Vector Machines and otherkernel-based methods, Cambridge Univ. Press (2000).
4. Scholkopf, B. and Smola, A. J., Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond, The MIT Press (2001).
5. Sutton R. S. and Barto, A. G., Reinforcement Learning: An Introduction, The MIT Press (2017).
6. Goodfellow, I., Bengio, Y., and Courville, A., Deep Learning, The MIT Press (2016).
7. Koller D. and Friedman, N., Probabilistic Graphical Models: Principles and Techniques, The MIT Press (2009).

Course Outcomes (COs):

CO1: Provide students with an in-depth knowledge of advanced machine learning concepts.

CO2: Introduce the mathematical and statistical concepts that form the basis of advanced machine learning models.

CO3: Foster critical thinking and problem-solving skills by challenging students to analyze and critique the strengths and limitations of advanced machine learning models in various applications and contexts.

MA625	Statistical Models and Analysis	3	0	0	3

An overview of basic probability theory and theory of estimation; Bayesian statistics; maximum a posteriori (MAP) estimation; conjugate priors; Exponential family; posterior asymptotics; linear statistical models; multiple linear regression: inference technique for the general linear model, generalised linear models: inference procedures, special case of generalised linear models leading to logistic regression and log linear models; introduction to non-linear modelling; sampling methods: basic sampling algorithms, rejection sampling, adaptive rejection sampling, sampling and the EM algorithm, Markhov chain, Monte Carlo, Gibbs sampling, slice sampling.

References:

1. Dobson, A. J. and Barnett, A. G., An Introduction to Generalised Linear Models, 3rd ed., Chapman and Hall/CRC (2008).
2. Krzanowski, W. J., An Introduction to Statistical Modeling, Wiley (2010).
3. Hastie, T., Tibshirani, R., and Friedman, J.,The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Springer (2002).
4. Bishop, C. M., Pattern Recognition and Machine Learning, Springer (2006).

Course Outcomes (COs):

CO1: Explain the theory of general linear models and generalized linear models.

CO2: Outline the algorithms used for estimation for these models and teach the methodology to test the sutability of a particular model with specific number of parameters.

CO3: Perform statistical analysis, such as estimation, hypothesis testing, and analysis of variance, under these models.

CO4: Teach the students how to choose an appropriate model that fits reasonably well to a particular practical problem and analyse it by using the methods and algorithms that they studied.

E02	**Elective II**	**3**	**0**	**0**	**3**

- **Refer list of Electives**

E03	**Elective III**	**3**	**0**	**0**	**3**

- **Refer list of Electives**

E04	**Elective IV**	**3**	**0**	**0**	**3**

- **Refer list of Electives**

MA642	Data Modeling Lab II	0	0	6	2

Big data analytics: Introduction to spark 2.0 & tensor flow, tools to assess the quality of big data analytics. Mini project on a topic related with data modeling.

Course Outcomes (COs):

CO1: Acquire skills to implement cutting-edge data modeling techniques.

CO2: Explore advanced methodologies and algorithms for data analysis and modeling.

CO3: Apply learned concepts to address complex challenges in diverse domains.

MA643	Statistical Modeling Lab	0	0	3	1

Course Outcomes (COs):

After doing this lab students will be able to model a given real life problem in terms of a proper statistical model using the available data and studied tools. During the Lab itself students take up a problem and formulate a suitable model to understand the behaviour of the model and do simulations so as to get a model which behaves in an optimal manner based on some objective function.

MA644	Advanced Machine Learning Lab	0	0	3	1

Course Outcomes (COs):

CO1: By working on programming assignments that focus on real-world problems, students will gain valuable skills and insights into the application of advanced machine-learning techniques across diverse domains.

CO2: Enhance students ability to debug and troubleshoot complex machine learning code, improving their overall programming proficiency.

CO3: Foster a culture of innovation by empowering students to apply their knowledge of emerging trends in advanced machine learning to propose and develop novel solutions to complex problems in diverse domains.

SEMESTER III

MA851	Seminar	0	0	0	1

MA852	Project Work – Phase I	0	0	0	14

SEMESTER IV

MA853	Project Work – Phase II	0	0	0	17

ELECTIVES FOR SEMESTER - I

MA869	Discrete Mathematics and Graph Theory	3 Credits

Basic counting principle: Pigeonhole principle, inclusion - exclusion principle, recurrence relations, generating functions. Fundamentals of logic, set theory, language, and finite state ma- chines.

Undirected and direct graphs, modelling with graphs, trial and cycle- Eulerian trial and Hamilton cycle, connectivity and trees. Graph algorithms: BFS, DFS, shortest path, optimal spanning trees, matching, job assignment problem, optimal transportation through flows in networks.

References:

1. Liu, C. L., Elements of Discrete Mathematics, 2nd Ed., Tata McGraw-Hill (2000).
2. Grivaldi, R. P. and Ramana, B. V., Discrete and Combinatorial mathematics, Pearson (2008).
3. Graham, R. L., Knuth, D. E., and Patashnik, O., Concrete Mathematics, 2nd Ed., Addison- Wesley (1994).
4. Rosen, K. H., Discrete Mathematics and its Applications, 6th Ed., Tata McGraw-Hill (2007).

Course Outcomes (COs):

CO1: Familiarize with counting principles

CO2: Learn concepts like, pegion hole principle, exclusion inclusion principle, recursive equations

CO3: Apply these concepts to specific problems

CO4: Familiarize with various of types graphical models, concepts of walk, trail, path, cycles. Then to learn, connected graph, tree, spanning tree, Eulerian trail, Hamiltonian path.

CO5: Learn various algorithms related to spanning tree, shortest path, Halls marriage theorem. Also, learn about their applications for optimization problems in real-life.

Online Swayam Course	Introduction to Internet of Things	3 Credits

Online Swayam Course	Introduction to Parallel Programming	3 Credits

ELECTIVES FOR SEMESTER – II

MA871	Advanced Kernel Methods	3 Credits

Theory of reproducing kernel Hilbert space, support vector machines, kernel ridge regession, kernel feature extraction, kernel online learning, Bayesian kernel methods, graph kernels, kernels for text, kernels for structured data.

References:

1. Bishop, C. M., Pattern Recognition and Machine Learning, Springer (2006).
2. Cristianini, N. and Shawe-Taylor, J., An Introduction to Support Vector Machines and other kernel-based methods, Cambridge Univ. Press (2000).
3. Scholkopf, B. and Smola, A. J., Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond, The MIT Press (2001).
4. Shawe-Taylor, J. and Cristianini, N., Kernel Methods for Pattern Analysis, Cambridge Univ. Press (2004)

Course Outcomes (COs):

CO1: Understanding the theoretical foundations: Students will develop a solid understanding of the theoretical foundations of kernel methods.

CO2: Implementing kernel-based algorithms: Students will learn how to implement kernel-based algorithms.

CO3: Applying kernel methods in real-world problems: The course will provide hands-on experience with applying kernel methods to real-world datasets and problems, preparing students to use them in their own research or projects.

MA872	Advanced Optimization	3 Credits

Unconstrained Optimization: line search method: Wolf condition, Goldstein condition, sufficient decrease and backtracking, Newtons method and Quazi Newton method; trust region method: the Cauchy point, algorithm based on Cauchy point, improving on the Cauchy point, the Dog- leg method, two-dimensional subspace reduction; nonlinear conjugate gradient method: the Fletcher Reeves method.
Constrained Optimization: penalty method, quadratic penalty method, convergence, non smooth penalty function, L1 penalty method, augmented Lagrangian method; quadratic programming, Schur complementary, null space method, active set method for convex QP; sequential quadratic programming, convex programming.

References:

1. Boyd, S. and Vandenberghe, L., Convex Optimization, Cambridge Univ. Press (2004).
2. Nocedel, J. and Wright, S. Numerical Optimization, Springer (2006).

Course Outcomes (COs):

CO1: Impart knowledge of advanced theory of optimization.

CO2: Familiarize with advanced algormths to solve optimization problems.

CO3: Write codes for optimization problems using advance algorimths.

MA873	Graphical and Deep Learning Models	3 Credits

Graphical Models: Basic graph concepts; Bayesian Networks; conditional independence; Markov Networks; Inference: variable elimination, belief propagation, max-product, junction trees, loopy belief propogation, expectation propogation, sampling; structure learning; learning with missing data.
Deep Learning: recurrent networks; probabilistic neural nets; Boltzmann machines; RBMs; sigmoid belief nets; CNN; autoencoders; deep reinforcement learning; generative adversarial net- works; structured deep learning; applications.

References:

1. Koller D. and Friedman, N., Probabilistic Graphical Models: Principles and Techniques, The MIT Press (2009).
2. Barber, D., Bayesian Reasoning and Machine Learning, Cambridge Univ. Press (2012).
3. Bishop, C. M., Pattern Recognition and Machine Learning, Springer (2006).
4. Hastie, T., Tibshirani, R., and Friedman, J., The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Springer (2002).
5. Murphy, K. P., Machine Learning: A Probabilistic Perspective, The MIT Press (2012).
6. Goodfellow, I., Bengio, Y., and Courville, A., Deep Learning, The MIT Press (2016).

Course Outcomes (COs):

CO1: Develop a comprehensive understanding of the fundamentals of graphical and deep learning models.

CO2: Cover key concepts, architectures, and principles underlying both graphical models and deep learning.

CO3: Learn the mathematical and statistical concepts that form the basis of graphical and deep learning models

MA867	Reinforcement Learning	3 Credits

The reinforcement learning problem; tabular & approximate solution methods: dynamic programming, Monto-Carlo Methods, temporal difference learning, eligibility traces; planning and learning; dimensions of reinforcement learning.

References:

1. Sutton R. S. and Barto, A. G., Reinforcement Learning: An Introduction, The MIT Press(2017).
2. Tesauro G., Temporal Difference Learning and TD-Gammon, Communications of the Association for Computing Machinery (1995).

MA874	Theory of Algorithms	3 Credits

Greedy and dynamic programming algorithms; Kruskals algorithm for minimum spanning trees; the folklore algorithm for the longest common subsequence of two strings; Dijstras algorithm and other algorithms for the shortest path problem; divide-and-conqueror and checkpoint algorithms; the Hirshbergs algorithm for aligning sequences in linear space; quick sorting; the Knuth-Morrison-Pratt algorithm; suffix trees; data structures: chained lists, reference lists, hash- ing; the Chomsky-hierarchy of grammars; parsing algorithms; connections to the automaton theory; Turing-machines; complexity and intractability; complexity of algorithms; the complexity classes P and NP. 3-satisfiability, and NP-complete problems; stochastic Turing machines; the complexity class BPP; counting problems; P, P-complete; FPRAS; discrete time Markov chains; reversible Markov chains; Frobenius theorem; relationship between the second largest eigenvalue modulus and convergence of Markov chains; upper and lower bounds on the second largest eigenvalue; the Sinclair-Jerrum theorem: relationship between approximate counting and sampling.

References:

1. Dasgupta, S. S., Papadimitriou, C. H., Vazirani, U. V., Algorithms, McGraw-Hill Higher Education (2006).
2. Kleinberg , J. and Tardos, E., Algorithm Design, Addison-Wesley (2006).
3. Cormen, T. H., Leiserson, C. E., Rivest, R. L., and Stein, C., Introduction to Algorithms, 3rd Ed., The MIT Press (2009).

MA875	Topological Data Analysis	3 Credits

Basics of Topology; complexes on data; homology; topological Persistence; computing Betti numbers; reconstruction from data; topology inference from data; computing optimized homology cycles; reeb graphs from data; topology of Laplace operators, spectra approximation.

References:

1. Edelsbrunner, H. and Harer, J. L., Computational Topology, American Mathematical Society(2010).
2. Dey, T. K., Curve and Surface Reconstruction: Algorithms with Mathematical Analysis, Cambridge Univ. Press (2011).
3. Hatcher, A., Algebraic Topology, Cambridge Univ. Press (2001).

Online Swayam Course	Cloud Computing	3 Credits