| | | | | Semester: V | | | | | | | | | |
|--|---|--|--|--|---|---|---|--|--|--|--|--|--|
| | | | MATHEMA | FICS FOR MACHI | NE LEARNING | | | | | | | | |
| | | | | (Theory) | | | | | | | | | |
| (Group B: Global Elective) | | | | | | | | | | | | | |
| Cour | rse Code | : | 18G5B17 | | CIE | : | 100 Marks | | | | | | |
| | lits: L:T:P | : | 3:0:0 | | SEE | : | 100 Marks | | | | | | |
| | | | | | | | | | | | | | |
| Total Hours:39LSEE Duration:3.00 HoursCourse Learning Objectives: The students will be able to | | | | | | | | | | | | | |
| 1 | Understand the basic knowledge on the fundamental concepts of linear algebra that form the | | | | | | | | | | | | |
| | foundation of machine intelligence. | | | | | | | | | | | | |
| 2 | Acquire practical knowledge of vector calculus and optimization to understand the machine learning | | | | | | | | | | | | |
| | algorithms or techniques. | | | | | | | | | | | | |
| 3 | Use the con | cept | s of probability | and distributions to | analyze possible | appli | cations of machine | | | | | | |
| | learning. | | | | | | | | | | | | |
| 4 | | | | d estimation to solve | | | | | | | | | |
| 5 | Analyze the | app | ropriate mathemat | tical techniques for | classification and | optim | ization of decision | | | | | | |
| | problems. | | | | | | | | | | | | |
| | | | | | | | | | | | | | |
| | | | | Unit-I | | | 07 Hrs | | | | | | |
| | ar Algebra: | | | | | | | | | | | | |
| | | | | Review of Vector Spaces-Linear Independence, Basis, Rank and Linear Mappings. Affine Spaces, Inner | | | | | | | | | |
| Products, Lengths and Distances, Angles and Orthogonality, Orthonormal Basis, Orthogonal Complement, | | | | | | | | | | | | | |
| | | | | | | Ortho | | | | | | | |
| | | | ons, Orthogonal Pr | ojections, Rotations, | | Ortho | osition. | | | | | | |
| Inner | Product of Fu | ncti | ons, Orthogonal Pr | ojections, Rotations, U nit – II | | Ortho | | | | | | | |
| Inner | Product of Fu | ncti nd (| ons, Orthogonal Pr Continuous Optim | ojections, Rotations, Unit – II lization: | Singular Value Dec | Ortho | 07 Hrs | | | | | | |
| Inner Vector Grad | Product of Fu or Calculus an ients of Vect | ncti nd (or-V | ons, Orthogonal Pr Continuous Optim Valued Functions, | ojections, Rotations, Unit – II ization: Gradients of Mati | Singular Value Dec | Ortho compo r Co | mputing Gradients, | | | | | | |
| Inner Vecto Grad Back | Product of Fu or Calculus an ients of Vect propagation ar | ncti nd (or-V nd A | ons, Orthogonal Pr Continuous Optim Valued Functions, utomatic Different | ojections, Rotations, Unit – II ization: Gradients of Matriciation, Linearization | Singular Value Dec rices, Identities for and Multivariate Ta | Ortho compo r Co ylor S | mputing Gradients, Series, Optimization | | | | | | |
| Inner Vecto Grad Back | Product of Fu or Calculus an ients of Vect propagation ar | ncti nd (or-V nd A | ons, Orthogonal Pr Continuous Optim Valued Functions, utomatic Different t, Constrained Opti | ojections, Rotations, Unit – II ization: Gradients of Mati- iation, Linearization imization and Lagran | Singular Value Dec rices, Identities for and Multivariate Ta | Ortho compo r Co ylor S | mputing Gradients, Series, Optimization ex Optimization. | | | | | | |
| Inner Vecto Grad Back Using | Product of Fu or Calculus an ients of Vect propagation ar g Gradient Des | ncti nd C or-V nd A | ons, Orthogonal Pr Continuous Optim Valued Functions, utomatic Different t, Constrained Opti | ojections, Rotations, Unit – II ization: Gradients of Matriciation, Linearization | Singular Value Dec rices, Identities for and Multivariate Ta | Ortho compo r Co ylor S | mputing Gradients, Series, Optimization | | | | | | |
| Inner Vecto Grad Back Using Prob | Product of Fu or Calculus an ients of Vect propagation ar g Gradient Des | ncti nd (or-V nd A scent | ons, Orthogonal Pr Continuous Optim /alued Functions, utomatic Different t, Constrained Opti U butions: | rojections, Rotations, Unit – II iization: Gradients of Matriciation, Linearization imization and Lagran Unit –III | Singular Value Dec rices, Identities for and Multivariate Ta ge Multipliers and C | Ortho compo r Con conve | mputing Gradients, Series, Optimization 08 Hrs | | | | | | |
| Inner Vecto Grad Back Using Prob Cons | er Product of Fu or Calculus and ients of Vect propagation ar g Gradient Des pability and Di struction of a H | ncti nd C or-V nd A scent scent stri | ons, Orthogonal Pr Continuous Optim Valued Functions, utomatic Different t, Constrained Opti U butions: ability Space, Disc | ojections, Rotations, Unit – II ization: Gradients of Matriciation, Linearization imization and Lagran Unit –III crete and Continuous | Singular Value Dec rices, Identities for and Multivariate Ta ge Multipliers and C | ortho compo r Cor cylor S Conve | mputing Gradients, Series, Optimization ex Optimization. 08 Hrs e, Product Rule and | | | | | | |
| Inner Vecto Grad Back Using Cons Baye | or Calculus and ients of Vect propagation ar g Gradient Des oblity and Di struction of a H es' Theorem, C | ncti nd C or-V nd A scent scent stri | ons, Orthogonal Pr Continuous Optim Valued Functions, utomatic Different t, Constrained Opti U butions: ability Space, Disc | rojections, Rotations, Unit – II iization: Gradients of Matriciation, Linearization imization and Lagran Unit –III | Singular Value Dec rices, Identities for and Multivariate Ta ge Multipliers and C | ortho compo r Cor cylor S Conve | mputing Gradients, Series, Optimization ex Optimization. 08 Hrs e, Product Rule and | | | | | | |
| Inner Vecto Grad Back Using Prob Cons Baye | er Product of Fu or Calculus and ients of Vect propagation ar g Gradient Des pability and Di struction of a H | ncti nd C or-V nd A scent scent stri | ons, Orthogonal Pr Continuous Optim Valued Functions, utomatic Different t, Constrained Opti U butions: ability Space, Disc sian Distribution, | rojections, Rotations, Unit – II ization: Gradients of Matriciation, Linearization imization and Lagran Unit –III crete and Continuous Conjugacy and the | Singular Value Dec rices, Identities for and Multivariate Ta ge Multipliers and C | ortho compo r Cor cylor S Conve | mputing Gradients, Series, Optimization ex Optimization. 08 Hrs e, Product Rule and ange of Variables - | | | | | | |
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| Inner Vector Grad Back Using Prob Cons Baye Inver | e Product of Fu or Calculus and ients of Vect propagation ar g Gradient Des oblity and Di struction of a H es' Theorem, C rse Transform. ar Regression | ncti nd C or-V nd A scen Frob Saus | ons, Orthogonal Pr Continuous Optim Valued Functions, utomatic Different t, Constrained Opti butions: ability Space, Disc sian Distribution, | ojections, Rotations, Unit – II ization: Gradients of Matriciation, Linearization imization and Lagran Unit –III crete and Continuous Conjugacy and the Unit –IV | Singular Value Dec rices, Identities for and Multivariate Ta ge Multipliers and C s Probabilities, Sum Exponential Family | ortho compo cylor S Conve a Rule 7, Cha | 07 Hrs 07 Hrs mputing Gradients, Series, Optimization 08 Hrs e, Product Rule and ange of Variables - 08 Hrs | | | | | | |
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| Inner Vecto Grad Back Using Prob Cons Baye Inver Lines Ortho Dens Gaus Persp Dimo | Product of Fu or Calculus and ients of Vect propagation are g Gradient Des obility and Di atruction of a H ess' Theorem, C rese Transform. ar Regression lem Formulation ogonal Projection sity Estimation sian Mixture In pective. | ncti nd Cor-V nd A scent Saus Frob Gaus Saus Saus Non. n wi Mod | ons, Orthogonal Pr Continuous Optim /alued Functions, utomatic Different t, Constrained Opti butions: ability Space, Dis- sian Distribution, Parameter Estim th Gaussian Mixt el, Parameter Lea tion with Principa mum Variance Pe | ojections, Rotations, Unit – II ization: Gradients of Matriation, Linearization imization and Lagran Unit –III crete and Continuous Conjugacy and the Unit –IV ation, Bayesian Lir ure Models: rning via Maximum Unit –V al Component Analy prespective, Projection | Singular Value Dec rices, Identities for and Multivariate Ta ge Multipliers and C s Probabilities, Sum Exponential Family near Regression, M Likelihood, EM Al | ortho compo- r Cor ylor S Conve a Rule 7, Cha daxin gorith | 05 07 Hrs 07 Hrs 07 Hrs mputing Gradients, Series, Optimization 08 Hrs 08 Hrs 08 Hrs e, Product Rule and ange of Variables - 08 Hrs 08 Hrs 08 Hrs num Likelihood as 08 Hrs num Likelihood as 09 Hrs or Computation and 09 Hrs | | | | | | |
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| Course | Course Outcomes: After completing the course, the students will be able to | | | | | | |
|-------------|--|--|--|--|--|--|--|
| CO1: | Explore the fundamental concepts of mathematics involved in machine learning techniques. | | | | | | |
| CO2: | Orient the basic concepts of mathematics towards machine learning approach. | | | | | | |
| CO3: | Apply the linear algebra and probability concepts to understand the development of different | | | | | | |
| | machine learning techniques. | | | | | | |
| CO4: | Analyze the mathematics concepts to develop different machine learning models to solve practical | | | | | | |
| | problems. | | | | | | |

Reference Books1Mathematics for Machine Learning, M. P. Deisenroth, A. A. Faisal and C. S. Ong, 1st Edition, 2020, Cambridge University Press.2Linear Algebra and Learning from Data, Gilbert Strang, 1st Edition, 2019, Wellesley Cambridge Press, ISBN: 0692196382, 9780692196380.3Introduction to Machine Learning, Ethem Alpaydin, 2nd Edition, 2010, PHI Publication, ISBN-978-81-203-4160-9.4The Elements of Statistical Learning, Trevor Hastie, Robert Tibshirani and Jerome Friedman, 2nd Edition, 2009, Springer, ISBN: 978-0-387-84857-0, 978-0-387-84858-7.

Continuous Internal Evaluation (CIE); Theory (100 Marks)

CIE is executed by the way of Tests (T), Quizzes (Q),) and Experiential Learning (EL). Three tests are conducted for 50 marks each and the sum of the marks scored from three tests is reduced to 50. Minimum of three quizzes are conducted and each quiz is evaluated for 10 marks adding up to 30 marks. All quizzes are conducted online. Faculty may adopt innovative methods for conducting quizzes effectively. The number of quizzes may be more than three also. The marks component for experiential learning is 20.

Total CIE is 50 (T) +30 (Q) +20 (EL) = 100 Marks.

Semester End Evaluation (SEE); Theory (100 Marks)

SEE for 100 marks is executed by means of an examination. The Question paper for the course contains two parts, Part – A and Part – B. Part – A consists of objective type questions for 20 marks covering the complete syllabus. Part – B consists of five main questions, one from each unit for 16 marks adding up to 80 marks. Each main question may have sub questions. The question from Units I, IV and V have no internal choice. Units II and III have internal choice in which both questions cover entire unit having same complexity in terms of COs and Bloom's taxonomy level.

| CO-PO Mapping | | | | | | | | | | | | |
|---------------|-----|-----|-----|-----|-----|-----|------------|-----|-----|------|------|------|
| CO/PO | PO1 | PO2 | PO3 | PO4 | PO5 | PO6 | PO7 | PO8 | PO9 | PO10 | PO11 | PO12 |
| CO1 | 3 | 2 | - | 1 | - | - | - | - | - | - | - | 2 |
| CO2 | 3 | 2 | 1 | - | - | - | - | - | - | - | - | 2 |
| CO3 | 2 | 3 | 2 | 2 | - | - | - | - | - | - | - | 1 |
| CO4 | 3 | 3 | 1 | 2 | 1 | - | - | - | - | - | - | 3 |

High-3: Medium-2: Low-1