**RTM Nagpur University, Nagpur**
**Four Year B.Tech. Course**
**(Revised Curriculum as Per AICTE Model)**
**B.Tech. VIII Semester (Computer Technology) Scheme**

| Elective –VI Social Networks | |
|---|---|
| **Total Credits: 3** | **Subject Code: BTCT801T-1** |
| Teaching Scheme :<br>Lectures: 03 Hours/Week<br>Tutorials: 0 Hours/Week<br>Practical: 0 Hours/Week | Examination Scheme :<br>Duration of University Exam: 03 Hrs.<br>College Assessment : 30 Marks<br>University Assessment:70 Marks |

**Course Objective:**

1 To understand highly interconnected and hence more complex social networks.
2 To represent connected social networks in form of graph.
3 To apply graph theory, sociology, game theory.
4 To use tools and extract statistics from social networks.

**Course Outcomes:**

At the end of this course student are able to:

1. Learn social networks , its types and representation
2. Understand weak ties, strong and weak relationships , homophily and calculate
3. Analyse links.
4. Understand Power Laws and Rich-Get-Richer Phenomena.
5. Understand Small World Phenomenon.

Week 1: Introduction

Week 2: Handling Real-world Network Datasets

Week 3: Strength of Weak Ties

Week 4: Strong and Weak Relationships (Continued) & Homophily

Week 5: Homophily Continued and +Ve / -Ve Relationships

Week 6: Link Analysis

Week 7: Cascading Behaviour in Networks

Week 8: Link Analysis (Continued)

Week 9: Power Laws and Rich-Get-Richer Phenomena

Week 10: Power law (contd..) and Epidemics

Week 11: Small World Phenomenon

Week 12: Pseudocore (How to go viral on web)

**References:**


1. https://onlinecourses.nptel.ac.in/noc23_cs19/preview
2. Networks, Crowds and Markets by David Easley and Jon Kleinberg, Cambridge University Press, 2010 (available for free download).
3. Social and Economic Networks by Matthew O. Jackson, Princeton University Press, 2010.

| Elective –VI Reinforcement Learning | |
|---|---|
| **Total Credits: 3** | **Subject Code: BTCT801T-2** |
| Teaching Scheme :<br>Lectures: 03 Hours/Week<br>Tutorials: 0 Hours/Week<br>Practical: 0 Hours/Week | Examination Scheme :<br>Duration of University Exam: 03 Hrs.<br>College Assessment : 30 Marks<br>University Assessment:70 Marks |

**Course Objective:**

1 It aims to model the trial-and-error learning process that is needed in many problem situations where explicit instructive signals are not available.
2 It has roots in operations research, behavioral psychology and AI.
3 The goal of the course is to introduce the basic mathematical foundations of reinforcement learning.
4 It highlight some of the recent directions of research.

**Course Outcomes:**

At the end of this course student are able to:

1. Understand Bandit algorithm and its mathematical formulation.
2. Use dynamic programming for reinforcement learning.
3. Perform function approximation and apply LSM.
4. Fit Q, DQN & Policy Gradient for Full RL.
5. Use combinatorial models for complex problems.

Week 1 Introduction
Week 2 Bandit algorithms – UCB, PAC
Week 3 Bandit algorithms –Median Elimination, Policy Gradient
Week 4 Full RL & MDPs
Week 5 Bellman Optimality
Week 6 Dynamic Programming & TD Methods
Week 7 Eligibility Traces
Week 8 Function Approximation
Week 9 Least Squares Methods
Week 10 Fitted Q, DQN & Policy Gradient for Full RL
Week 11 Hierarchical RL
Week 12 POMDPs

**References:**


1. https://archive.nptel.ac.in/courses/106/106/106106143/
2. R. S. Sutton and A. G. Barto. Reinforcement Learning - An Introduction. MIT Press. 1998

| Elective –VI GPU Architectures and Programming | |
|---|---|
| **Total Credits: 3** | **Subject Code: BTCT801T-3** |
| Teaching Scheme :<br>Lectures: 03 Hours/Week<br>Tutorials: 0 Hours/Week<br>Practical: 0 Hours/Week | Examination Scheme :<br>Duration of University Exam: 03 Hrs.<br>College Assessment : 30 Marks<br>University Assessment:70 Marks |

**Course Objective:**

1 To introduce basics of conventional CPU architectures, their extensions for single instruction multiple data processing (SIMD).
2 To understand concept in the form of single instruction multiple thread processing (SIMT) as is done in modern GPUs.
3 To teach architecture specific details.
4 To introduce different architecture-aware optimization techniques relevant to both CUDA and OpenCL.

**Course Outcomes:**

At the end of this course student are able to:

1 Understand conventional CPU architectures, their extensions for single instruction multiple data processing (SIMD).
2 Program in CUDA about data space & synchronization.
3 Apply optimization on kernals, thtreads etc.
4 Learn basics of OpenCL.
5 Design an application using neural networks.

Week 1: Review of Traditional Computer Architecture – Basic five stage RISC Pipeline, Cache Memory, Register File, SIMD instructions

Week 2: GPU architectures - Streaming Multi Processors, Cache Hierarchy, The Graphics Pipeline

Week 3: Introduction to CUDA programming

Week 4: Multi-dimensional mapping of dataspace, Synchronization

Week 5: Warp Scheduling, Divergence

Week 6: Memory Access Coalescing

Week 7: Optimization examples : optimizing Reduction Kernels

Week 8: Optimization examples : Kernel Fusion, Thread and Block Coarsening

Week 9: OpenCL basics

Week 10: CPU GPU Program Partitioning

Week 11: Application Design : Efficient Neural Network Training/Inferencing

Week 12: Application Design : Efficient Neural Network Training/Inferencing,cont'd

**References:**


1. https://onlinecourses.nptel.ac.in/noc23_cs61/preview.
2. "Computer Architecture -- A Quantitative Approach" - John L.Hennessy and David A. Patterson
   "Programming Massively Parallel Processors" - David Kirk and Wen-mei Hwu.
3. Heterogeneous Computing with OpenCL" -- Benedict Gaster,Lee Howes, David R. Kaeli.

| Elective –VII Predictive Analytics-Regression and Classification | |
|---|---|
| **Total Credits: 3** | **Subject Code: BTCT802T-1** |
| Teaching Scheme :<br>Lectures: 03 Hours/Week<br>Tutorials: 0 Hours/Week<br>Practical: 0 Hours/Week | Examination Scheme :<br>Duration of University Exam: 03 Hrs.<br>College Assessment : 30 Marks<br>University Assessment:70 Marks |

**Course Objective:**

1 The course will provide an overview of fundamental ideas in statistical predictive models.
2 The objective is to understand how statistical models handle prediction problems.
3 The stress will be on understanding the construction of the models and implementation.
4 It is a core course if students aspire to be Data Scientists.

**Course Outcome:**

At the end of this course student are able to:

1 Understand predictive models, LSM, Normal equations and GMT.
2 Understand regression models and infer its statistical inference.
3 Check model assumptions and bias variance tradeoff.
4 Perform regression analysis in various programming languages.
5 Apply regression models and classification for predictive analysis.

**Week 1:**
- Landscape of the predictive models.
- Least Squares method

**Week 2:**
- Normal Equations:
- Gauss Markov theorem

**Week 3:**
- The geometry of Regression Model and Feature Engineering
- Statistical Inference of Regression Coefficient

**Week 4:**
- Checking Model Assumptions
- Model Comparison with R-squared, RMSE, AIC or BIC

**Week 5:**
- Model Complexity and Bias-Variance tradeoff
- Feature selection and Dimension Reduction

**Week 6:**
- Multicollinearity and Variance Inflation Factor
- Regularization with LASSO, Ridge and Elastic Net
- Ridge Regression with Python

**Week 7:**
- Regression Analysis with Python
- Regression Analysis with R
- Regression Analysis with Julia

**Week 8:** Major Applications of Regression Models
- Capital Asset Pricing Model
- Bootstrap Regression
- Time Series Forecasting with Regression Model
- Granger Causal model.

**Week 9:**
- Logistic Regression
- MLE of coefficient of Logistic Regression

**Week 10:**
- Fit Logistic Regression with optim function in R
- Fit Logistic Regression with glm function in R
- Fit Logistic Regression with sklearn in Python
- Fit Logistic Regression in Julia

**Week 11:**
- Logistic Regression and Inference
- Discriminant Analysis

**Week 12:**
- Multinomial Logit Regression
- Generalised Linear Regression
- Poisson Regression
- Negative Binomial Regression

**References:**


1. https://onlinecourses.nptel.ac.in/noc23_ma46/preview.
2. An Introduction to Statistical Learning by James, Witten, Hastie, and Tibshirani, Springer (https://www.statlearning.com/).
3. The Elements of Statistical Learning by Hastie, Tibshirani, and Friedman, Springer (https://hastie.su.domains/Papers/ESLII.pd).
4. Regression and Other Stories by Gelman, Hill, and Vehtari, by Cambridge University Press (https://avehtari.github.io/ROS-Examples/).

| Elective –VII Block Chain and its Application | |
|---|---|
| **Total Credits: 3** | **Subject Code: BTCT802T-2** |
| Teaching Scheme :<br>Lectures: 03 Hours/Week<br>Tutorials: 0 Hours/Week<br>Practical: 0 Hours/Week | Examination Scheme :<br>Duration of University Exam: 03 Hrs.<br>College Assessment : 30 Marks<br>University Assessment:70 Marks |

**Course Objective**:

1. Learn its capability of providing a transparent, secured, tamper-proof solution for interconnecting different stakeholders in a trustless setup
2. This subject will cover the basic design principles of Blockchain technology and its applications over different sectors
3. Additionally, the course also provides tutorials on setting up blockchain applications using one of the well-adopted permissionless blockchain platforms - Ethereum, and one permissioned blockchain platform - Hyperledger
4. Provide its applications

**Course Outcomes:**

At the end of this course student are able to:

1. Understand basic crypto primitives.
2. Understand elements and evolution of blockchain.
3. Understand consensus in permission less and permissioned models.
4. Hands on ethereum smart contracts and hyperledgers.
5. Perform decentralized identity management, interoperability.

Week 1: Introduction to Blockchain Technology and its Importance

Week 2: Basic Crypto Primitives I – Cryptographic Hash

Week 3: Basic Crypto Primitives II – Digital Signature

Week 4: Evolution of the Blockchain Technology

Week 5: Elements of a Blockchain

Week 6: Blockchain Consensus I – Permissionless Models

Week 7: Blockchain Consensus II – Permissioned Models

Week 8: Smart Contract Hands On I – Ethereum Smart Contracts (Permissionless Model)

Week 9: Smart Contract Hand On II – Hyperledger Fabric (Permissioned Model)

Week 10: Decentralized Identity Management

Week 11: Blockchain Interoperability

Week 12: Blockchain Applications

**References:**


1. Mastering Blockchain: A deep dive into distributed ledgers, consensus protocols, smart contracts, DApps, cryptocurrencies, Ethereum, and more, 3rd Edition, Imran Bashir, Packt Publishing, 2020, ISBN: 9781839213199, book website: https://www.packtpub.com/product/mastering-blockchain-third-edition/9781839213199.
2. Hyperledger Tutorials - https://www.hyperledger.org/use/tutorials.
3. Ethereum Development Resources - https://ethereum.org/en/developers.
4. Online materials and case studies.

| Elective –VII Data Analytics using Python | |
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| **Total Credits: 3** | **Subject Code: BTCT802T-3** |
| Teaching Scheme :<br>Lectures: 03 Hours/Week<br>Tutorials: 0 Hours/Week<br>Practical: 0 Hours/Week | Examination Scheme :<br>Duration of University Exam: 03 Hrs.<br>College Assessment : 30 Marks<br>University Assessment:70 Marks |

**Course Objectives:**

1. To learn analytics using python programming language.
2. Learn hypothesis testing and ANOVA model.
3. Regression models and its implementation.
4. Learn clustering and classification.

**Course Outcomes:**

At the end of this course student are able to:

1. Understand data analytics and Python fundamentals.
2. Perform sampling using various methods and perform hypothesis test or ANOVA test.
3. Fit linear regression model and calculate various errors.
4. Apply ROC.
5. Apply clustering and classification using python programming

Week 1: Introduction to data analytics and Python fundamentals

Week 2: Introduction to probability

Week 3: Sampling and sampling distributions

Week 4: Hypothesis testing

Week 5: Two sample testing and introduction to ANOVA

Week 6: Two way ANOVA and linear regression

Week 7: Linear regression and multiple regressions

Week 8: Concepts of MLE and Logistic regression

Week 9: ROC and Regression Analysis Model Building

Week 10: $c^2$ Test and introduction to cluster analysis

Week 11: Clustering analysis

Week 12: Classification and Regression Trees (CART)

**References:**


1. https://archive.nptel.ac.in/courses/106/107/106107220/
2. McKinney, W. (2012). Python for data analysis: Data wrangling with Pandas, NumPy, and IPython. " O'Reilly Media, Inc.".
3. Swaroop, C. H. (2003). A Byte of Python. Python Tutorial.
4. Ken Black, sixth Editing. Business Statistics for Contemporary Decision Making. "John Wiley & Sons, Inc".
5. Anderson Sweeney Williams (2011). Statistics for Business and Economics. "Cengage Learning".
6. Douglas C. Montgomery, George C. Runger (2002). Applied Statistics & Probability for Engineering. "John Wiley & Sons, Inc"
7. Jay L. Devore (2011). Probability and Statistics for Engineering and the Sciences. "Cengage Learning".
8. David W. Hosmer, Stanley Lemeshow (2000). Applied logistic regression (Wiley Series in probability and statistics). "Wiley-Interscience Publication".
9. Jiawei Han and Micheline Kamber (2006). Data Mining: Concepts and Techniques. "
10. Leonard Kaufman, Peter J. Rousseeuw (1990). Finding Groups in Data: An Introduction to Cluster Analysis. "John Wiley & Sons, Inc".