25CSC431 NATURAL LANGUAGE PROCESSING 3-0-0-3

Course Objectives

- This course is devoted to the study of phonological, morphological, and syntactic processing. These areas will be approached from both a linguistic and an algorithmic perspective.
- The course will focus on the computational properties of natural languages and the algorithms used to process them, as well as the match between grammar formalisms and the linguistic data that needs to be covered.

Course Outcomes

CO1: Understand the models, methods, and algorithms of statistical Natural Language Processing (NLP) for
common NLP tasks.
CO2: Understand mathematical and statistical models for NLP.
CO3: Understand linguistic phenomena and linguistic features relevant to each NLP task.
CO4: Develop probabilistic models for NLP.
CO5: Apply learning models to NLP tasks such as document summarization, machine translation, sentiment
analysis and spell checking

CO-PO Mapping

PO/PSO CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2
CO1	3	2	2	3									3	2
CO2	3	2	3	2									3	2
CO3	3	2	3	2									3	2
CO4	3	1	2	2	3								3	2
CO5	3	1	2	2	3								3	2

Syllabus

Unit 1

Introduction- History of NLP, Study of Human languages, ambiguity, Phases in natural language processing, applications. Textual sources and Formats. Linguistics resources- Introduction to the corpus, elements in the balanced corpus, (examples -TreeBank, PropBank, WordNet, VerbNet, etc.) Word Level analysis - Regular expressions, Morphological parsing, Types of Morphemes. Tokenization, N-grams, Stemming, Lemmatization, Spell checking. Management of linguistic data with NLTK.

Unit 2

Syntactic Analysis – Lexeme, phonemes, phrases and idioms, word order, agreement, tense, aspect and mood and agreement, Context Free Grammar, and spoken language syntax. Parsing-Unification, probabilistic parsing. Part of Speech tagging- Rule-based POS tagging, Stochastic POS tagging, Transformation-based tagging (TBL), Handling of unknown words, named entities, and multi-word expressions.

Semantics Analysis- Meaning representation, semantic analysis, lexical semantics, WordNet - WordNet similarity measures., Synsets and Hypernyms, Word Sense Disambiguation- Selectional restriction, machine learning approaches, dictionary-based approaches.

Unit 3

Discourse- Reference resolution, constraints on co-reference, an algorithm for pronoun resolution, text coherence, discourse structure. Information Retrieval-Types of an information retrieval model, Boolean Model, Vector space model-Word2Vec, BERT, Improving user queries. Machine Translation – EM algorithm - Discriminative learning - Deep representation learning - Generative learning.

Applications of NLP- Machine translation, Document Summarization, sentiment Analysis, ChatGPT4

Textbook(s)

Martin JH, Jurafsky D. "Speech and language processing: An introduction to natural language processing, computational linguistics, and speech recognition". Pearson Publication, Second Edition; 2013.

Reference(s)

James A. "Natural language Understanding", Second Edition, Pearson Education; 2002.

Bharati A., Sangal R., Chaitanya V."Natural language processing: a Paninian perspective", PHI; 2000.

Tiwary U S, Siddiqui T. "Natural language processing and information retrieval". Oxford University Press, Inc.; 2008.

Steven Bird, Ewan Klein, Edward Loper, "Natural Language Processing with Python – Analyzing Text with the Natural Language Toolkit" (O'Reilly 2009, website 2018)

Evaluation Pattern: 70:30

Assessment	Internal	End Semester
Midterm	20	
Continuous Assessment – Theory (*CAT)	10	
Continuous Assessment – Lab (*CAL)	40	
**End Semester		30 (50 Marks; 2 hours exam)

*CAT – Can be Quizzes, Assignments, and Reports

*CAL – Can be Lab Assessments, Project, and Report

**End Semester can be theory examination/ lab-based examination/ project presentation

25CSC432	ARTIFICIAL INTELLIGENCE AND ROBOTICS	3-0-0-3

Course Objectives

- This course aims to make the students understand the basic principles in AI and robotics technologies.
- The students will be able to apply machine learning algorithms for applications using AI and robotics.

Course Outcomes

CO1: Understand the fundamentals of robots and their components.
CO2: Design and develop kinematic operation for a robotic manipulator.
CO3: Understand different algorithms for path planning and navigation.
CO4: Apply AI and Robotics technologies using basic programming and machine learning.
CO5: Understand societal and business impact of AI and Robotics technologies.

CO-PO Mapping

PO/PSO CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2
CO1	3	2	2	2	1	1	1	1	1	2	1	1	3	2
CO2	3	2	3	2	2	2	1	2	1	2	2	2	3	2
CO3	3	2	3	2	3	2	2	2	2	2	2	2	3	2
CO4	3	1	2	3	3	2	2	2	2	2	2	2	3	2
CO5	3	1	2	2	3	1	2	2	2	2	2	2	3	2

Syllabus

Unit 1
Introduction, Actuators and drives, Control components, De-mining Robot: Embedded Robot Controller, I/O Interface, and PWM Amplifiers, control software, sensor inputs, sensors.

Unit 2
Kinematics, differential motion, statics, energy method, hybrid position force control, Non-holonomic systems, dynamics - Translational and Rotational, computed torque control, Transformation, Path Planning, and Trajectories, Time Response of Dynamic Systems, Dynamic Effects of Feedback Control, Control Systems - Artificial Intelligence based optimal control, Applications of Machine Learning and Deep learning in robot navigation.

Unit 3

Numerical Optimization, Dynamic Optimal Control, Parameter Estimation and Adaptive Control, Application of Computer vision in robotics, Tele-robotics and virtual reality.

Textbook(s)

Asada H, Slotine JJ. "Robot analysis and control". John Wiley & Sons; 1986.

Reference(s)

Iosifidis, Alexandros, and Anastasios Tefas, eds. "Deep Learning for Robot Perception and Cognition". Academic Press, 2022.
Yoshikawa, Tsuneo. "Foundations of robotics: analysis and control". MIT press, 2003.
Spong MW. Seth Hutchinson and Mathukumalli Vidyasagar. "In Robot modeling and control"; 2020.
Lynch KM, Park FC. "Modern Robotics". First Edition, Cambridge University Press, 2017.
John JC. "Introduction to robotics: mechanics and control". Third Edition, Pearson publication, 2004.
Kelly A. "Mobile robotics: mathematics, models, and methods". Cambridge University Press; 2013.
Thrun S, Burgard W, Fox D. "Probabilistic robotics". MIT press; 2005.
Siciliano B, Khatib O. "Handbook of robotics. Section kinematic loops";2008.
Richard S. Sutton, Andrew G. Barto, Francis Bach, "Reinforcement Learning: An Introduction", MIT Press, 2018.

Evaluation Pattern: 70:30

Assessment	Internal	End Semester
Midterm	20	
Continuous Assessment – Theory (*CAT)	10	
Continuous Assessment – Lab (*CAL)	40	
**End Semester exam		30 (50 Marks; 2 hours exam)

*CAT – Can be Quizzes, Assignments, and Reports
*CAL – Can be Lab Assessments, Project, and Report
**End Semester can be theory examination/ lab-based examination/ project presentation

25CSC433	NEURAL NETWORKS AND DEEP LEARNING	3-0-0-3

Course Objectives

- This course provides an introduction to deep neural network models and explores applications of these models.
- The course covers feedforward networks, convolutional networks, recurrent and recursive networks, as well as general topics such as input encoding and training techniques.

Course Outcomes

CO1: Understand the learning components of neural networks and apply standard neural network models to
learning problems.
CO2: Analyze the learning strategies of deep learning – regularization, generalization, optimization, bias and
variance.
CO3: Analyze regular deep learning models for training, testing and validation in standard datasets.
CO4: Apply neural networks for deep learning using standard tools.
CO5: Understand the mathematics for Deep learning.

CO-PO Mapping

PO/PSO / CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2
CO1	3	2	2	3	-	-	-	-	-	-	-	-	3	2
CO2	3	2	3	2	2	-	-	-	-	-	-	-	3	2
CO3	3	2	3	2	3	-	-	-	-	-	-	-	3	2
CO4	3	1	2	1	2	-	-	-	-	-	-	-	3	2
CO5	3	1	2	1	-	-	-	-	-	-	-	-	3	2

Syllabus

Unit 1
Perceptrons – classification - limitations of linear nets and perceptrons - multi-Layer Perceptrons (MLP); Activation functions - linear, softmax, tanh, ReLU; error functions; Feed-forward networks - Backpropagation - recursive chain rule (backpropagation); Learning weights of a logistic output -Loss functions - learning via gradient descent; Optimization – momentum method; Adaptive learning rates – RMSProp - mini-batch gradient descent; Bias-variance trade off - Regularization - overfitting - inductive bias – drop out - generalization.

Unit 2
Convolutional Neural Networks - Basics and Evolution of Popular CNN architectures; CNN Applications: Object Detection and Localization, Face Recognition, Neural Style Transfer
Recurrent Neural Networks - GRU - LSTM – Transformers Networks; Applications: NLP and Word Embeddings, Attention Models,

Unit 3

Restricted Boltzmann Machine, Deep Belief Networks, Auto Encoders and Applications: Semi-Supervised classification, Noise Reduction, Non-linear Dimensionality Reduction; Introduction to GAN - Encoder/Decoder, Generator/Discriminator architectures; Challenges in NN training - Data Augmentation - Hyper parameter Settings; Transfer Learning - Developing and Deploying ML Models (e.g., Tensor Flow/PyTorch)

Textbook(s)

Ian Goodfellow, Yoshua Bengio and Aaron Courville. "Deep Learning", MIT Press, Second Edition; 2016.

Reference(s)

Koller, D. and Friedman, N. "Probabilistic Graphical Models". MIT Press;2009.
Hastie, T., Tibshirani, R. and Friedman, J. "The Elements of Statistical Learning". Second edition, Springer; 2009.
Bishop, C. M. "Neural Networks for Pattern Recognition". Oxford University Press;1995.
Aggarwal, Charu C. "Neural networks and deep learning." Springer, 2018.

Evaluation Pattern: 70:30

Assessment	Internal	External
Midterm	20	
Continuous Assessment – Theory (*CAT)	10	
Continuous Assessment – Lab (*CAL)	40	
**End Semester		30 (50 Marks; 2 hours exam)

*CAT – Can be Quizzes, Assignments, and Reports
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**End Semester can be theory examination/ lab-based examination/ project presentation

25CSC434	COMPUTATIONAL INTELLIGENCE	3-0-0-3

Course Objectives

- This course gives importance to make the students to understand the concepts of different computational methodologies to bring computational intelligence.
- This course covers learning the basics of Neural Network, Fuzzy Logic and Evolutionary Algorithms.
- This course also enables the student design and implement simple algorithms with Neural Network, Fuzzy Logic and Evolutionary Algorithms.

Course Outcomes

CO1: Understand the nature and purpose of different computational intelligent components.
CO2: Apply neural networks and applications in real-world scenarios.
CO3: Understand fuzzy systems in application scenarios.
CO4: Analyze the working of Evolutionary algorithms in optimization problems.
CO5: Apply Evolutionary approaches to application scenarios.

CO-PO Mapping

PO/PSO CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2
CO1	3	2	2	2	1	1	1	-	-	-	-	-	3	2
CO2	3	2	2	2	2	2	2	-	-	-	-	-	3	2
CO3	3	2	2	2	1	2	2	-	-	-	-	-	3	2
CO4	3	1	2	2	3	1	1	-	-	-	-	-	3	2
CO5	3	1	2	2	3	2	2	-	-	-	-	-	3	2

Syllabus

Unit 1
Brief review – Pitfalls of Traditional AI – Why computational intelligence? – Computational Intelligence concept, Neural Networks – single layer and multilayer, Backpropagation, Radial-Basis Function Networks, Recurrent Neural Networks.

Unit 2
Fuzzy sets, properties, membership function, fuzzy operations. Fuzzy logic and fuzzy inference and applications.
Evolutionary computation – constituent algorithms, Collective Intelligence - Swarm intelligence algorithms – Overview of other bio-inspired algorithms

Unit 3

Hybrid approaches (neural networks, fuzzy logics, genetic algorithm, etc) - Applications of Computational intelligence in Industrial applications, manufacturing and logistics - Fuzzy systems and Evolutionary algorithms.

Textbook(s)

David B Fogel, Derong Liu, James M Keller. "Fundamentals of Computational Intelligence: Neural Networks, Fuzzy Systems, and Evolutionary Computation". John Wiley & Sons; 2016

Konar A, 'Computational Intelligence: Principles, Techniques and Applications", Springer Verlat, 2005.

Reference(s)

Siddique, Nazmul, and Hojjat Adeli. "Computational intelligence: synergies of fuzzy logic, neural networks and evolutionary computing". John Wiley & Sons, 2013.

Lam, Hak-Keung, and Hung T. Nguyen, eds. "Computational intelligence and its applications: evolutionary computation, fuzzy logic, neural network and support vector machine techniques". World Scientific, 2012.

Eberhart RC, Shi Y. "Computational intelligence: concepts to implementations". Elsevier; 2007

Karray F, Karray FO, De Silva CW. "Soft computing and intelligent systems design: theory, tools, and applications. Pearson Education", First Edition, Pearson India, 2009.

Engelbrecht AP. "Computational intelligence: an introduction". John Wiley & Sons; 2007.

Evaluation Pattern: 70:30

Assessment	Internal	End Semester
Midterm	20	
Continuous Assessment – Theory (*CAT)	10	
Continuous Assessment – Lab (*CAL)	40	
**End Semester		30 (50 Marks; 2 hours exam)

*CAT – Can be Quizzes, Assignments, and Reports

*CAL – Can be Lab Assessments, Project, and Report

**End Semester can be theory examination/ lab-based examination/ project presentation

25CSC435	GENERATIVE AI	3-0-0-3

Course Objectives

- This course covers the mathematical and computational foundations of generative modeling, as well as applications.
- Specific topics include variational autoencoders, generative adversarial networks, autoregressive models such as Transformers, normalizing flow models, information lattice learning, neural text decoding, prompt programming, and detection of generated content.

Course Outcomes

CO1: Understand principles of Generative AI and their applications.
CO2: Analyze Autoencoder and transformer in real-world scenarios.
CO3: Analyze GAN architectures and applications.
CO4: Analyze graphs for probabilistic models.

CO-PO Mapping

PO/PSO / CO	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO10	PO11	PO12	PSO 1	PSO 2
CO1	3	3	3	3	2	0	3	2	2	2	0	0	3	3
CO2	3	3	3	3	3	0	3	2	2	2	0	0	3	3
CO3	3	3	3	3	3	0	3	2	2	2	0	0	3	3
CO4	3	3	3	3	3	0	3	2	2	2	0	0	3	3

Syllabus

Unit 1
Introduction to Generative AI, Autoencoders – Representational power, layer size and depth, Undercomplete autoencoders, Denoising autoencoders, Contractive autoencoders, Variational autoencoders, Case study: Applications of autoencoders in dimension reduction.

Unit 2
Generative Adversarial networks (GAN) – structure and training algorithm, Deep Convolutional GAN, Autoregressive models – Finite memory, long range memory through RNN and CNN, Transformers – Encoder, decoders, scaling laws, Case study: Generative Adversarial Networks-aided Intrusion Detection System.

Unit 3

Structured probabilistic models – Issues of unstructured models, Directed and Undirected Graphs to describe the models, Partition function, separation and D-separation, Conversion of graphs, sampling from graphical models, Case study: Restricted Boltzmann machine.

Textbook(s)

I. Goodfellow, Y. Bengio, and A. Courville, "Deep Learning", MIT Press, 2016.

Reference(s)

Raut, R., Pathak, P. D., Sakhare, S. R., & Patil, S. (Eds.), "Generative Adversarial Networks and Deep Learning: Theory and Applications". CRC Press, 2023.

J. M. Tomcsak, "Deep Generative Modeling", Springer, 2022.

Langr J, Bok V. "GANs in action: deep learning with generative adversarial networks". Manning. 2019.

A. Papoulis and S. U. Pillai, "Probability - Random Variables, and Stochastic Processes", Fourth Edition, McGraw-Hill, 2017.

Evaluation Pattern: 70:30

Assessment	Internal	End Semester
Midterm	20	
Continuous Assessment – Theory (*CAT)	10	
Continuous Assessment – Lab (*CAL)	40	
**End Semester		30 (50 Marks; 2 hours exam)

*CAT – Can be Quizzes, Assignments, and Reports

*CAL – Can be Lab Assessments, Project, and Report

**End Semester can be theory examination/ lab-based examination/ project presentation

25CSC436	CONVERSATIONAL AI	3-0-0-3

Course Objectives

- This course relates the principles and practice of creating AI conversational interface systems.
- This course includes knowledge-rich natural language understanding, multimodal interaction (speech and sketching), principles of dialogue drawn from cognitive science, question-answering, and architectures for building conversational systems.

Course Outcomes

CO1: Understand computational models of dialogue systems.
CO2: Understand architectures for building conversational systems.
CO3: Apply problem-solving dialogue model for question answering.
CO4: Analyze dialogue management and chatbots.

CO-PO Mapping

PO/PSO / CO	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO10	PO11	PO12	PSO 1	PSO 2
CO1	3	2	2	2	1	0	0	2	3	2	0	0	3	3
CO2	3	2	2	2	1	0	0	2	3	2	0	0	3	3
CO3	3	3	3	3	3	0	0	2	3	2	0	0	3	3
CO4	3	3	3	3	3	0	0	2	3	2	0	0	3	3

Syllabus

Unit 1
Introduction to Conversational AI, Principles of dialogue - common ground, sub dialogues, Gricean principles of conversation, Computational models of dialogue systems, Chatbots architectures – Rule-based and Corpus based, Case study: Sounding board

Unit 2
Architecture for dialogue systems: Pipelines behind common assistant programs, collaborative problem-solving model, dialogue acts. cognitive architectures, Question Answering: Sources of knowledge, Case Study: IBM’s Deep Q/A approach

Unit 3
Dialog Management and System Evaluation, Dialog Manager Architectures, Natural Language Generation, evaluation of performance, reward propagation. Case study: Social chatbot evaluation

Textbook(s)

Seminck, O., Michael McTear."Conversational AI: Dialogue Systems, Conversational Agents, and Chatbots", Computational Linguistics, 2023.

Reference(s)

Tur, G. and De Mori, R., "Spoken language understanding: Systems for extracting semantic information from speech". John Wiley & Sons. 2011.

Jokinen, K. and McTear, M., "Spoken dialogue systems. Synthesis Lectures on Human Language Technologies", vol. 2, no. 1, 2009.

Evaluation Pattern: 70:30

Assessment	Internal	End Semester
Midterm	20	
Continuous Assessment – Theory (*CAT)	10	
Continuous Assessment – Lab (*CAL)	40	
**End Semester		30 (50 Marks; 2 hours exam)

*CAT – Can be Quizzes, Assignments, and Reports

*CAL – Can be Lab Assessments, Project, and Report

**End Semester can be theory examination/ lab-based examination/ project presentation

25CSC437	REINFORCEMENT LEARNING	3-0-0-3

Course Objectives

- This course primarily focuses on training students to frame reinforcement learning problems and to tackle algorithms from dynamic programming, Monte Carlo and temporal-difference learning.
- It involves larger state space environments using function approximation, deep Q-networks and state-of-the-art policy gradient algorithms.

Course Outcomes

CO1: Understand Markov decision process and reinforcement learning.
CO2: Apply AI search, planning, and learning.
CO3: Apply Hierarchical learning techniques.
CO4: Analyze Q-learning and multi-agent systems.

CO-PO Mapping

PO/PSO CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2
CO1	3	2	3	3	2	0	0	2	2	2	0	0	3	3
CO2	3	2	3	3	3	0	0	2	2	2	0	0	3	3
CO3	3	2	3	3	3	0	0	2	2	2	0	0	3	3
CO4	3	2	3	3	3	0	0	2	2	2	0	0	3	3

Syllabus

Unit 1
Introduction to Reinforcement learning, Markov Decision Process (MDP) - Markov Process, Markov Reward Process, Markov Decision Process and Bellman Equations, Partially Observable MDPs, Planning by Dynamic programming (DP) - Policy Evaluation, Value Iteration, Policy Iteration, DP Extensions, model-free prediction and control.

Unit 2
Integrating planning with learning - Model-based RL, Integrated Architecture and Simulation-based Search, Monte-Carlo (MC) Learning, Exploration and exploitation - Multi-arm Bandits, Contextual Bandits and MDP Extensions, integrating AI search and learning - Classical Games: Combining Minimax Search and RL.

Unit 3

Hierarchical RL - Semi-Markov Decision Process, Learning with Options, Deep RL - Proximal Policy Optimization (PPO), Deep Deterministic Policy Gradient (DDPG), Double Q-Learning, Multi-agent RL - Cooperative vs. Competitive Settings, Mixed Setting.

Textbook(s)

Richard S. Sutton and Andrew G. Barto; "Reinforcement Learning: An Introduction"; 2nd Edition, MIT Press, 2018.

Reference(s)

Dimitri P. Bertsekas; "Reinforcement Learning and Optimal Control"; 1st Edition, Athena Scientific, 2019.

Dimitri P. Bertsekas; "Dynamic Programming and Optimal Control (Vol. I and Vol. II)"; 4th Edition, Athena Scientific, 2017.

Csaba Szepesvári; "Algorithms of Reinforcement Learning (Synthesis Lectures on Artificial Intelligence and Machine Learning)", Morgan & Claypool Publishers, 2010.

Evaluation Pattern: 70:30

Assessment	Internal	End Semester
Midterm	20	
Continuous Assessment – Theory (*CAT)	10	
Continuous Assessment – Lab (*CAL)	40	
**End Semester		30 (50 Marks; 2 hours exam)

*CAT – Can be Quizzes, Assignments, and Reports

*CAL – Can be Lab Assessments, Project, and Report

**End Semester can be theory examination/ lab-based examination/ project presentation

25CSC438	MACHINE LEARNING WITH GRAPHS	3-0-0-3

Course Objectives

- This course aims to equip students with a solid foundation in the theory and applications of machine learning with graphs, as well as practical skills in implementing and applying GNNs to real-world problems.
- By the end of the course, students should be able to understand and use various GNN architectures and techniques to solve graph-based machine learning problems.

Course Outcomes

CO1: Develop an understanding of the theory and applications of machine learning with graphs.

CO2: Gain an understanding of various GNN architectures and techniques.

CO3: Acquire practical skills in implementing and applying GNNs to solve real-world problems.

CO4: Be able to handle large graphs and solve graph-based machine learning problems using GNNs.

CO-PO Mapping

PO/PSO CO	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2
CO1	3	3	1	0	1	2	1	0	0	0	0	0	3	2
CO2	3	3	1	0	1	2	1	0	0	0	0	0	3	2
CO3	3	3	1	2	3	2	1	0	0	0	1	1	3	2
CO4	3	3	2	2	3	2	1	0	0	0	0	0	3	2

Syllabus

Unit 1

Introduction to Machine Learning for Graphs, Structure of Graphs, Node Embeddings, Random graphs with arbitrary degree distributions and their applications, Properties of Networks, and Random Graph Models, Motifs and Structural Roles in Networks, Simple Building Blocks of Complex Networks, Community Structure in Networks, Fast unfolding of communities in large networks, Overlapping Community Detection at Scale: A Nonnegative Matrix Factorization Approach, Spectral Clustering, Message Passing and Node Classification, Graph Representation Learning

Unit 2

Theory of Graph Neural Networks, Architectures-GCN, GAT, MPNN & Design Space, Deep Generative Models for Graphs, Link Analysis: PageRank, Network Effects and Cascading Behaviour, Probabilistic Contagion and Models of Influence, Influence Maximization in

Networks, Outbreak Detection in Networks, Network Evolution, Reasoning over Knowledge Graphs, Applications of Graph Neural Networks

Unit 3

Efficient Graphlet Kernels for Large Graph Comparison, Semi-Supervised Classification with Graph Convolutional Networks, Inductive Representation Learning on Large Graphs ,Graph Attention Networks, GNN Augmentation and Training, Hierarchical Graph Representation Learning with Differentiable Pooling, Machine Learning with Heterogeneous Graphs, Modeling Relational Data with Graph Convolutional Networks, Heterogeneous Graph Transformer, Advanced Topics in GNNs, Algorithm for Training Deep and Large Graph Convolutional Networks

Textbook(s)

William L. Hamilton, "Graph Representation Learning", McGill University 2020.
David Easley and Jon Kleinberg, "Networks, Crowds, and Markets: Reasoning About a Highly Connected World", Cambridge University Press (2010).

Reference(s)

Negro, Alessandro. "Graph-powered machine learning". Simon and Schuster, 2021.
Pósfai, Márton, and Albert-Laszlo Barabasi. "Network Science". Cambridge, UK: Cambridge University Press, 2016.

Evaluation Pattern: 70:30

Assessment	**Internal**	**End Semester**
Mid Term Exam	20	
Continuous Assessment – Theory (*CAT)	20	
Continuous Assessment – Lab (*CAL)	30	
**End Semester		30 (50 Marks; 2 hours exam)

*CAT – Can be Quizzes, Assignments, and Reports
*CAL – Can be Lab Assessments, Project, and Report
**End Semester can be theory examination/ lab-based examination/ project presentation

25MAT431 INTRODUCTION TO GEOSTATISTICS AND GIS 3-0-0-3

Course Outcomes

CO1: Understanding of spatial data, its types and how to handle it.
CO2: Map generation and its understanding in a GIS software (including open-source software)
CO3: Fundamentals of spatial statistics and introduction to R software
CO4: Time series analysis in geospatial datasets

Unit I

Cartography & GIS: Intro to Geographic Information Systems (GIS) and their applications; Vector and Raster data operations. Spatial phenomena and its distribution, diversity of representation forms, map types, scale, projections, coordinate system. Concepts of map making: Data Posting, symbolizations, typography; Contour Map; primary and derivative map, features and resolution. Map making ArcGIS, digitization.

Unit II

Google Earth: Exporting vector and raster maps to KML; Reading KML files through R, obtaining data via Google service, export of maps to Google Earth. Google Earth Engine (GEE): Introduction to online GIS, Data repository of GEE, basic data extraction and analysis, automated workflows using remote sensing.

Unit III

Spatial statistics: Conventional Analysis (non-geostatistical), Why Geostatistics, Environmental variables, source of spatial variability, deterministic and scholastic processes. Analysis of discrete and continuous random variables. probability density function; Variances, joint variation, covariance, correlation, regression, different types of error like root mean square.

Unit IV

Probability theory: Univariate, bivariate, multivariate statistics, Gaussian Distribution, Central Limit Theorem, Variogram Statistics, Nugget, Higher Dimensions & Statistical Anisotropy, Model-Fitting “Rules of Thumb”. Hands-on different R tools like gstat, geoR.

Unit V

Time series analysis: Examples of time series; Purposes of analysis; Components (trend, cycle, seasonal, irregular); Stationarity and autocorrelation; Approaches to time series analysis; Simple descriptive methods: smoothing, decomposition; Regression.

Skills acquired: Practical knowledge of GIS software, statistical and time series analysis of geospatial data using python

TEXTBOOKS/REFERENCES:

1. Islam, T., Srivastava, P. K., Gupta, M., Zhu, X., & Mukherjee, S. (Eds.). (2014). *Computational intelligence techniques in earth and environmental sciences*. Springer Netherlands.

2. Wackernagel, H. (2013). *Multivariate geostatistics: an introduction with applications*. Springer Science & Business Media.

3. Chun, Y., & Griffith, D. A. (2013). *Spatial statistics and geostatistics: theory and applications for geographic information science and technology*. Sage.