MCSC106: SOFTWARE TOOLS AND TECHNIQUES [0-0-2]

Course Objective:

To develop proficiency in the use of software tools required for project development.

Course Learning Outcomes:

On completing this course, the student will be able to:

CO1: master the command line interface
CO2: use features of version control systems
CO3: debug and profile code
CO4: manage dependencies

Syllabus:

Shell Tools and Scripting, Editors (Vim), Data Wrangling, Command-line Environment, Version Control (Git), Debugging and Profiling, Metaprogramming: Working with Daemons, FUSE, Backups, APIs, Common command-line flags/patterns, Window managers, VPNs, Markdown, Booting + Live USBs, Docker, Vagrant, VMs, Cloud, OpenStack, Notebook programming

Readings:

1. Newham C. Learning the bash shell: **Unix shell programming**. " O'Reilly Media, Inc."; 2005 Mar 29.
2. Shotts W. **The Linux command line: a complete introduction**. No Starch Press; 2019 Mar 5.
3. https://git-scm.com/book/en/v2

PART - I (SEMESTER - II)

MCSC201: ARTIFICIAL NEURAL NETWORKS [3-0-1]

Course Objectives: The course covers state-of-the-art techniques in neural network design, optimization, and specialized architectures. Students will gain hands-on experience through practical assignments and projects, enabling them to apply advanced neural network models to real-world problems.

Course Learning Outcomes:

On completion of this course, the student will be able to:

CO1: implement and analyze kernel methods, radial-basis function networks, and kernel regression.

CO2: implement and evaluate regularization networks and self-organizing maps.

CO3: develop information-theoretic models for the machine learning tasks.

Syllabus:

Unit I Kernel Methods and Radial-Basis Function Networks: Cover's Theorem on the Separability of Pattern, The Interpolation Problem, Radial-Basis-Function Networks, Recursive Least-Squares Estimation of the Weight Vector, Hybrid Learning Procedure for RBF Networks, Interpretations of the Gaussian Hidden Units, Kernel Regression and Its Relation to RBF Networks
Unit II Regularization Theory: Hadamard's Conditions for Well-Posedness, Tikhonov's Regularization Theory, Regularization Networks, Generalized Radial-Basis-Function Networks, The Regularized Least-Squares Estimator, Estimation of the Regularization Parameter, Manifold Regularization, Differentiable Manifolds, Generalized Regularization Theory, Laplacian Regularized Least-Squares Algorithm
Unit III Self-Organizing Maps: Two Basic Feature-Mapping Models, Self-Organizing Map, Properties of the Feature Map, Contextual Maps, Hierarchical Vector Quantization, Kernel Self-Organizing Map, Relationship Between Kernel SOM and Kullback–Leibler Divergence.
Unit IV Information-Theoretic Learning Models: Entropy, Maximum-Entropy Principle, Mutual Information, Copulas, Mutual Information as an Objective Function to be Optimized, Maximum Mutual Information Principle, Infomax and Redundancy Reduction, Spatially Coherent Features, Spatially Incoherent Features, Independent-Components Analysis, Sparse Coding of Natural Images and Comparison with ICA Coding, Natural-Gradient Learning for Independent-Components Analysis, Maximum-Likelihood Estimation for Independent-Components Analysis, Maximum-Entropy Learning for Blind Source Separation, Maximization of Negentropy for Independent-Components Analysis, Coherent Independent-Components Analysis, Rate Distortion Theory and Information Bottleneck, Optimal Manifold Representation of Data**.**
Unit V Stochastic Methods Rooted in Statistical Mechanics: Statistical Mechanics, Markov Chains, Metropolis Algorithm, Simulated Annealing, Gibbs Sampling, Boltzmann Machine, Logistic Belief Nets, Deep Belief Nets, Deterministic Annealing, Analogy of Deterministic Annealing with Expectation-Maximization Algorithm

Readings:

1. Simon O. Haykin, **Neural Networks and Learning Machines,** Pearson Education, 3rd Edition, 2016
2. C. M. Bishop, **Pattern Recognition and Machine Learning**, Springer, 2010.

MCSC202: DEEP LEARNING [3-0-1]

Course Objectives: The student learns various state-of-the-art deep learning algorithms and their applications to solve real-world problems. The student develops skills to design neural network architectures and training procedures using various deep learning platforms and software libraries.

Course Learning Outcomes:

On completing this course, the student will be able to:

CO1: describe the feedforward and deep networks.

CO2:design single and multi-layer feed-forward deep networks and tune various hyper-parameters.

CO3: analyze the performance of deep networks.

Syllabus:

Unit-I Introduction: Historical context and motivation for deep learning; deep feedforward neural networks, regularizing a deep network, model exploration, and hyperparameter tuning.

Unit-II Convolution Neural Networks: Introduction to convolution neural networks: stacking,