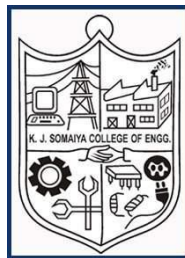




**Syllabus**  
**Honour Programme in**  
**Artificial Intelligence**  
Offered by Department of Information Technology

**From**  
**Academic Year 2021-22**  
**Revision 1**  
(Approved in Academic Council meeting dated      )



**K J Somaiya College of Engineering, Mumbai-77**  
( A Constituent College of Somaiya Vidyavihar University)

## **Honour Degree Programme in Artificial Intelligence**

Offered by Department of Information Technology

### **Abstract:**

Artificial intelligence (AI) is part and parcel of daily routine. Now a days AI is used for face recognition, robots, Alexa, driver less cars, recommendations on Netflix and Amazon. It powers Google's search engine, the diagnostic aiding tools for healthcare, predictive models and enables Facebook for target advertising to autonomous weapons that can kill without human intervention.

This honours program develops familiarity with programming for AI applications with a solid foundation by covering the basic Machine and Deep learning terminologies. The program gives insight to Deep Network architecture design, regularization and optimization. Further this stretches an opportunity to explore the convolutional networks and develop comprehension regarding Recurrent and Recursive Networks. This also spreads AI ethics for good AI with vision of the good life for the society. It will cover fundamental such as sounds, words, sentences, meanings, and conversations in context with Natural Language Processing (NLP).

### **Objectives:**

The offered program aims to

- Build the techniques and applications of Artificial Intelligence Design, implement, and evaluate a computing-based solution to meet requirement of real life problems.
- Provide understanding of data analytics and covering classical approach of Machine learning ranging from supervised learning to Neural Networks.
- Inculcate AI ethical issues including privacy concerns, responsibility, delegation of decision making and ethical practices.
- Provide an introduction to the field of computational linguistics, aka Natural Language Processing.

### **Learning Outcomes:**

At the successful completion of this Honor program, students will be able to

1. Realize problems with uncertainty, formalize the problem and find its solutions.
2. Comprehend data visualization, apply concepts of various types of learnings, Deep neural networks and its applications.
3. Understand the moral status of AI and synthesize the ethical issues raised by AI application.
4. Interpret words forms and semantics of NLP, apply Deep learning algorithms for NLP.

**Eligibility Criteria:**

Student who has earned all credits of First Year of Engineering in department of Information Technology

**Assessment Methods:** Tests, Mini projects, Laboratory, Presentation/ Video making, Quiz, study of research papers etc.

**Somaiya Vidyavihar University**  
**K. J. Somaiya College of Engineering, Mumbai -77**  
(A Constituent College of Somaiya Vidyavihar University)

**Credit Scheme**

<b>Course Code</b>	<b>Course Name</b>	<b>Teaching Scheme (Hrs.) TH – P – TUT</b>	<b>Total (Hrs.)</b>	<b>Credits Assigned TH – P – TUT</b>	<b>Total Credits</b>	<b>Semester of Major Degree</b>
116h66C301	Fundamental ofData Science	3 – 0 – 0	03	3 – 0 – 0	3	III
116h66L301	Fundamental ofData Science Laboratory	0 – 2 – 0	02	0 – 1 – 0	1	III
116h66C401	Introduction to Artificial Intelligence	3 – 0 – 0	03	3 – 0 – 0	3	IV
116h66L401	Introduction to Artificial Intelligence Laboratory	0 – 2 – 0	02	0 – 1 – 0	1	IV
116h66C501	MachineLearning	3 – 0 – 0	03	3 – 0 – 0	3	V
116h66L501	Machine Learning Laboratory	0 – 2 – 0	02	0 – 1 – 0	1	V
116h66C601	Deep Learning	3 – 0 – 0	03	3 – 0 – 0	3	VI
116h66L601	Deep Learning Laboratory	0 – 2 – 0	02	0 – 1 – 0	1	VI
116h66C701	Natural Language Processing	3 – 0 – 0	03	3 – 0 – 0	3	VII
116h66L701	Natural Language Processing Laboratory	0 – 2 – 0	02	0 – 1 – 0	1	VII
<b>Total</b>		<b>15 – 10 – 00</b>	<b>25</b>	<b>15 – 05 – 00</b>	<b>20</b>	<b>--</b>

**Examination Scheme**

Course Code	Course Name	Examination Scheme & Marks							
		CA		ESE	TW	O	P	P&O	Total
		ISE	IA						
116h66C301	Fundamental of Data Science	30	20	50	--	--	--	--	100
116h66L301	Fundamental of Data Science Laboratory	--	--	--	25	25	--	--	50
116h66C401	Introduction to Artificial Intelligence	30	20	50	--	--		--	100
116h66L401	Introduction to Artificial Intelligence Laboratory	--	--	--	25	25	--	--	50
116h66C501	Machine Learning	30	20	50	--	--		--	100
116h66L501	Machine Learning Laboratory	--	--	--	25	25	--	--	50
116h66C601	Deep Learning	30	20	50	--	--		--	100
116h66L601	Deep Learning Laboratory	--	--	--	25	25	--	--	50
116h66C701	Natural Language Processing	30	20	50	--	--		--	100
116h66L701	Natural Language Processing Laboratory	--	--	--	25	25	--	--	50
<b>Total</b>		150	100	200	125	100	--	--	750

Course Code	Course Title							
116h66C301	Fundamentals of Data Science							
	TH		P		TUT		Total	
Teaching Scheme(Hrs.)	03		--		--		03	
Credits Assigned	03		--		--		03	
Examination Scheme	Marks							
	CA		ESE	TW	O	P	P&O	Total
	ISE	IA						
	30	20	50	--	--	--	--	100

**Course prerequisites:** Basic concepts of databases

**Course Objectives:** This course includes the processes essential to perform initial investigations on data so as to discover patterns, to spot anomalies, to test hypotheses and to check assumptions with the help of summary statistics and visual representations. Also, it covers the techniques to optimize the parameters required in classification approach. It attempts to understand the data first and then efforts can be applied to extract as many insights from it using different visualization tools.

**At the end of successful completion of the course the student will be able to**

CO1: Summarize the data

CO2: Comprehend descriptive and proximity measures of data

CO3: Apply the transformations required on data to make it suitable for Mining

CO4: Comprehend various data visualization techniques and its

Module No.	Unit No.	Details	Hrs	COs
<b>1</b>	<b>Introduction to data</b>		<b>6</b>	<b>CO1</b>
	<b>1.1</b>	Understanding data, Types of attributes, Nominal, ordinal, interval, ratio, Discrete and continuous attributes		
	<b>1.2</b>	Types of datasets: Record data, Graph-based data, Sequence data, time series data, spatial data, General characteristics of datasets		
	<b>1.3</b>	Data quality problems, issues related to applications, •Data transformations to make data suitable for data mining, Exploratory Data Analysis vs. classical data analytics		
	<b>1.4</b>	Categorization of Data Analytics techniques, Supervised Unsupervised, semi-supervised, Application of Data science in real world: Medical and healthcare, Agriculture, disaster management etc.		
<b>2.</b>	<b>Exploring data using descriptive measures</b>		<b>12</b>	<b>CO2</b>
	<b>2.1</b>	Frequency distribution : simple, grouped, cumulative and relative frequency distribution, graphs for frequency distribution (Histogram, frequency polygon, frequency curve, cumulative frequency curve)		
	<b>2.2</b>	Measures of central tendency: Mean (Arithmetic, weighted and geometric mean), , median, mode, mid range • Predicting missing data using regression modeling, interpolation		
	<b>2.3</b>	Measures of dispersion: range, inter-quartile range, variance, standard deviation, root mean square deviation, Coefficients of dispersion based upon range, quartile deviation, mean deviation, standard deviation, ANOVA. • Boxplot, Quantile–Quantile Plot, Scatter Plots/Pair-plot and its limitations Data Correlation, Covariance, Bregman divergence. Measures of Skewness: Pearson’s coefficient, Bowley’s coefficient, coefficient based upon moments		
<b>3.</b>	<b>Data similarity and dissimilarity</b>		<b>9</b>	<b>CO2</b>
	<b>3.1</b>	Similarity measures for numeric data, Minkowski distance, Euclidean distance, Manhattan distance, supremum distance, Mahalanobis distance, Bhattacharyya distance		
	<b>3.2</b>	Similarity measures for symmetric and asymmetric binary data, simple matching coefficient, Jaccard coefficient, hamming distance		
	<b>3.3</b>	Similarity measures for textual data, edit distance, cosine distance, Jaro distance, n-Gram distance , longest		

		common subsequence, Dissimilarity between attributes of mixed type		
<b>4.</b>	<b>Data normalization, discretization and reduction techniques</b>		<b>10</b>	<b>CO3</b>
	<b>4.1</b>	Data Normalization, Min-Max normalization, z-score normalization, Decimal scaling		
	<b>4.2</b>	Data discretization, Binning, Histogram, discretization using data clustering techniques, discretization using classification techniques		
	<b>4.3</b>	Data reduction, filtering techniques, sampling techniques, attribute subset selection techniques, detecting outliers		
	<b>4.4</b>	Parameter Optimization techniques : Linear optimization and nonlinear optimization		
<b>5</b>	<b>• Data Visualization and interpretation</b>		<b>8</b>	<b>CO4</b>
	<b>5.1</b>	Pixel Oriented visualization techniques, Geometric projection visualization techniques, Icon based visualization techniques, Hierarchical visualization techniques		
	<b>5.2</b>	Visualizing complex data and Relations, Scoreboard Vs Dashboard, Graph Vs Chart		
	<b>5.3</b>	Data Visualization tools: Weka, Rapid Miner		
<b>Total</b>			<b>45</b>	



**Recommended Books:**

<b>Sr. No.</b>	<b>Name/s of Author/s</b>	<b>Title of Book</b>	<b>Name of Publisher with country</b>	<b>Edition and Year of Publication</b>
<b>1.</b>	S.C. Gupta , V. K. Kapoor	<i>Fundamentals of mathematical statistics</i>	Sultan Chand and Sons	2014
<b>2.</b>	P. N. Tan, M. Steinbach, Vipin Kumar,	<i>Introduction to Data Mining</i>	Pearson Education,	2014
<b>3.</b>	Han, Kamber	<i>Data Mining Concepts and Techniques</i>	Morgan Kaufmann	3 <sup>rd</sup> Edition, 2012
<b>4.</b>	C. B. Gupta, Vijay Gupta	<i>An Introduction to Statistical Methods</i>	Sultan Chand and Sons	23rd Edition, 2004
<b>5.</b>	Colin Ware	<i>Information Visualization: Perception for Design</i>	MK publication	May 2020, 4 <sup>th</sup> Edition
<b>6.</b>	Michael Berry and Gordon Linoff	<i>Data Mining Techniques</i>	Wiley Publications	2nd Edition , 2011

- Instructor needs to provide additional resources to students for in-depth understanding and practical applicability of the indicated topic/topics.

Course Code	Course Title							
116h66L301	Fundamental of Data Science Laboratory							
	TH			P		TUT		Total
Teaching Scheme(Hrs.)	-			02		-		02
Credits Assigned	-			01		-		01
Examination Scheme	Marks							
	CA		ESE	TW	O	P	P&O	Total
	ISE	IA						
	-	-	-	25	25	-	-	50

- Term-Work will consist of practical performance during the lab sessions covering the entire syllabus of “Fundamental of Data Science Laboratory”, Students will be graded based on continuous assessment of their term work.
- Oral Examination will be based on laboratory work and the entire syllabus of “Fundamental of Data Science Laboratory”.

Course Code	Course Title							
116h66C401	Introduction to Artificial Intelligence							
	TH			P		TUT		Total
Teaching Scheme(Hrs.)	03			-		-		03
Credits Assigned	03			-		-		03
Examination Scheme	Marks							
	CA		ESE	TW	O	P	P&O	Total
	ISE	IA						
	30	20	50	-	-	-	-	100

**Course prerequisites:** Mathematics- Probability Theory, Data structure, Analysis of Algorithms

**Course Objectives:**

This course introduces basic principles, techniques, and applications of Artificial Intelligence. The course coverage includes knowledge representation, logic, inference, problem solving, search algorithms, game theory, perception, learning, planning, and agent design. Students will develop familiarity with programming for AI applications.

**Course Outcomes :**

**At the end of successful completion of the course the student will be able to**

- CO1:** Understand structure, types and PEAS parameters of an AI (Artificial Intelligence) agent and formalize the problem.
- CO2:** Analyze and formalize the problem (as a state space, graph, etc.) and select the appropriate search method and write the algorithm
- CO3:** Ability to formally state the problem and develop the appropriate proof for given a logical deduction problem
- CO4 :** Comprehend problems with uncertainty, formalize the problem and understand how solutions are found
- CO5 :** Understand fundamentals of learning in AI

<b>Module No.</b>	<b>Unit No.</b>	<b>Details</b>	<b>Hrs.</b>	<b>CO</b>
<b>1</b>	<b>Introduction to AI and Intelligent Agents</b>		<b>05</b>	<b>CO1</b>
	<b>1.1</b>	Introduction to AI, AI Problems and AI techniques		
	<b>1.2</b>	Intelligent agents, Types of Agents		
	<b>1.3</b>	Agent Environments PEAS representation for an Agent		
	<b>1.4</b>	Solving problems by searching, Problem Formulation		
<b>2</b>	<b>Uninformed , Informed and Adversarial Search Techniques</b>		<b>12</b>	<b>CO2</b>
	<b>2.1</b>	Uninformed search, DFS, BFS, Uniform cost search, Depth Limited Search, Iterative Deepening, Bidirectional search, Comparing different techniques		
	<b>2.2</b>	Informed search, Heuristic functions, Best First Search, Greedy BFS, A* Crypto-Arithmetic Problem, CSP and Backtracking for CSP, Performance Evaluation		
	<b>2.3</b>	• Local search algorithms and optimization problems, Hill Climbing, Simulated Annealing, Genetic algorithms		
	<b>2.4</b>	• Game Playing, Min-Max Search, Alpha Beta pruning		
	<b>2.5</b>	• Defining constraint satisfaction problems(CSP), constraint propagation, backtracking search for CSPs		
<b>3</b>	<b>Knowledge and Reasoning</b>		<b>08</b>	<b>CO3</b>
	<b>3.1</b>	A Knowledge Based Agent, Wumpus world Environment, Logic, Propositional Logic, Propositional theorem proving,		
	<b>3.2</b>	Syntax and semantics of first-order logic, propositional vs. First-order inference, Unification and Lifting		
	<b>3.3</b>	• Forward and Backward Chaining, Resolution		
<b>4</b>	<b>Uncertain Knowledge and Reasoning</b>		<b>10</b>	<b>CO4</b>
	<b>4.1</b>	Acting under uncertainty, Basic probability notation, Inference using full joint distributions, Bayes' rule and its use.		
	<b>4.2</b>	Representing knowledge in an uncertain domain, Semantics of Bayesian networks, Efficient representation of conditional distributions		
	<b>4.3</b>	• Exact inference in Bayesian networks		
<b>5</b>	<b>• Learning</b>		<b>10</b>	<b>CO5</b>
	<b>5.1</b>	nework for Symbol-Based Learning, Version Space Search, The ID3 Decision Tree Induction Algorithm, Inductive Bias and Learnability		
	<b>5.2</b>	Knowledge and Learning, Unsupervised Learning, Reinforcement Learning		
	<b>5.3</b>	Prediction Error, Bias Error, Variance Error, Irreducible Error, The Bias-Variance Trade-off, Intro to fitting		
<b>Total</b>			<b>45</b>	

**Recommended Books:**

<b>Sr. No.</b>	<b>Name/s of Author/s</b>	<b>Title of Book</b>	<b>Name of Publisher with country</b>	<b>Edition and Year of Publication</b>
1.	Stuart Russell and Peter Norvig	<i>Artificial Intelligence: A Modern Approach</i>	Pearson, 2004	3 <sup>rd</sup> Edition
2.	Luger, George F.	<i>Artificial intelligence : structures and strategies for complex problem solving</i>	Pearson Education, 2009	6 <sup>th</sup> Edition
3.	Jason Brownlee.	<i>Master Machine Learning Algorithms</i>	eBook, 2017	Edition, v1.12
4.	Patrick H. Winston	<i>Artificial Intelligence</i>	Pearson Education, 1992	3 <sup>rd</sup> Edition

- Instructor needs to provide additional resources to students for in-depth understanding and practical applicability of the indicated topic/topics.

Course Code	Course Title							
116h66L401	Introduction to Artificial Intelligence Laboratory							
	TH			P	TUT			Total
Teaching Scheme(Hrs.)	-			02	-			02
Credits Assigned	-			01	-			01
Examination Scheme	Marks							
	CA		ESE	TW	O	P	P&O	Total
	ISE	IA						
	-	-	-	25	25	-	-	50

- Term-Work will consist of practical performance during the lab sessions covering the syllabus of “Introduction to Artificial Intelligence”, Students will be graded based on continuous assessment of their term work.
- Oral Examination will be based on laboratory work and the syllabus of “Introduction to Artificial Intelligence”.

Course Code	Course Title							
116h66C501	Machine Learning							
	TH		P		TUT		Total	
Teaching Scheme(Hrs.)	03		-		-		03	
Credits Assigned	03		-		-		03	
Examination Scheme	Marks							
	CA		ESE	TW	O	P	P&O	Total
	ISE	IA						
	30	20	50	-	-	-	-	100

**Course prerequisites:** Mathematics- Probability Theory, Calculus and Metrics

**Course Objectives:**

The course offers insightful introduction paving way to machine learning methods. The course covers classical approach of Machine learning ranging from supervised learning to neural Network and also includes dimensionality reduction approaches.

**Course Outcomes:**

**At the end of successful completion of the course the student will be able to**

**CO1:** Comprehend basics of machine learning

**CO2:** Apply concepts of different types of Learning and Neural Network

**CO3:** Comprehend radial-basis-function (RBF) networks and Kernel learning method

<b>Module No.</b>	<b>Unit No.</b>	<b>Details</b>	<b>Hrs.</b>	<b>CO</b>
<b>1</b>	<b>Introduction to Machine Learning</b>		<b>08</b>	<b>CO1</b>
	<b>1.1</b>	Introduction, Types of Machine Learning, Process of Machine learning		
	<b>1.2</b>	Introduction to terminologies – Weight space, Curse of Dimensionality		
	<b>1.3</b>	Testing Machine Learning Algorithms		
	<b>1.4</b>	Minimizing Risk algorithm and The Naïve Bayes' Classifier		
	<b>1.5</b>	Bias-Variance Trade Off		
<b>2</b>	<b>Linear Model for Classification</b>		<b>10</b>	<b>CO2</b>
	<b>2.1</b>	Linear Basis Function Models		
	<b>2.2</b>	Bayesian Linear Regression		
	<b>2.3</b>	Discriminant Functions		
	<b>2.4</b>	Probabilistic Generative Models		
	<b>2.5</b>	Probabilistic Discriminative Models		
<b>3</b>	<b>Neurons, Neural Networks, and Linear Discriminants</b>		<b>07</b>	<b>CO2</b>
	<b>3.1</b>	Hebb's Rule, McCulloch and Pitts Neurons and its limitation		
	<b>3.2</b>	The Perceptron		
	<b>3.3</b>	Linear Separability		
	<b>3.4</b>	Linear regression		
<b>4</b>	<b>• Dimensionality Reduction and Probabilistic Learning</b>		<b>10</b>	<b>CO3</b>
	<b>4.1</b>	Linear Discriminant Analysis (LDA)		
	<b>4.2</b>	Principle Component Analysis (PCA)		
	<b>4.3</b>	Independent Component Analysis (ICA)		
	<b>4.4</b>	The Expectation-Maximization (EM) Algorithm		
	<b>4.5</b>	Nearest Neighbor Methods		
<b>5</b>	<b>• Kernel Methods and Radial-Basis Function Networks</b>		<b>10</b>	<b>CO3</b>
	<b>5.1</b>	Cover's Theorem on the Separability of Patterns		
	<b>5.2</b>	The Interpolation Problem		
	<b>5.3</b>	Radial-Basis-Function Networks		
	<b>5.4</b>	K-Means Clustering		
	<b>5.5</b>	Recursive Least-Squares Estimation of the Weight Vector		
	<b>5.6</b>	Hybrid Learning Procedure for RBF Networks		
	<b>5.7</b>	The Support Vector Machine Viewed as a Kernel Machine		
	<b>5.8</b>	Design of Support Vector Machines		
<b>Total</b>			<b>45</b>	



**Recommended Books:**

<b>Sr. No.</b>	<b>Name/s of Author/s</b>	<b>Title of Book</b>	<b>Name of Publisher with country</b>	<b>Edition and Year of Publication</b>
1.	Stephen Marsland	<i>Machine learning An Algorithmic Perspective</i>	CRC Press, 2015	2 <sup>nd</sup> Edition
2.	Christopher M. Bishop	<i>Pattern Recognition and Machine Learning</i>	Springer Science, Business Media	2006
3.	Simon Haykin	<i>Neural Networks and Learning Machines</i>	Pearson Education	2009
4.	Alex Smola and S.V.N. Vishwanathan	<i>Introduction to Machine Learning</i>	Cambridge University Press	2008

- Instructor needs to provide additional resources to students for in-depth understanding and practical applicability of the indicated topic/topics.

Course Code	Course Title							
116h66L501	Machine Learning Laboratory							
	TH		P		TUT		Total	
Teaching Scheme(Hrs.)	-		02		-		02	
Credits Assigned	-		01		-		01	
Examination Scheme	Marks							
	CA		ESE	TW	O	P	P&O	Total
	ISE	IA						
	-	-	-	25	25	-	-	50

- Term-Work will consist of practical performance during the lab sessions covering the syllabus of “Machine Learning”, Students will be graded based on continuous assessment of their term work.
- Oral Examination will be based on laboratory work and the syllabus of “Machine Learning”.

Course Code	Course Title							
116h66C601	Deep Learning							
	TH		P	TUT			Total	
Teaching Scheme(Hrs.)	03		-	-			03	
Credits Assigned	03		-	-			03	
Examination Scheme	Marks							
	CA		ESE	TW	O	P	P&O	Total
	ISE	IA						
	30	20	50	--	--	--	--	100

**Course prerequisites:** Mathematics- Probability Theory, Calculus and Metrics.

**Course Objectives:**

The course builds a solid foundation by covering the basic deep terminologies. The course gives insight to Deep Network architecture design, regularization and optimization. Further students get an opportunity to explore the convolutional networks. The course helps to develop comprehension regarding Recurrent and Recursive Networks.

**Course Outcomes:**

**At the end of successful completion of the course the student will be able to**

**CO1:** Understand the evolution of Deep Learning.

**CO2:** Comprehend the Deep Network concepts.

**CO3:** Assimilate fundamentals of Convolutional Neural Network.

**CO4:** Underhand the essentials of Recurrent and Recursive Nets.

Module No.	Unit No.	Details	Hrs.	CO
1	<b>From Machine Learning to Deep Learning</b>		<b>10</b>	<b>CO1</b>
	1.1	Math Behind Machine Learning: Statistics, Probability Conditional Probabilities, Posterior Probability, Distributions, Samples Versus Population, Resampling Methods, Selection Bias, Likelihood		
	1.2	Bayesian Statistics, Supervise and Unsupervised Learning		
	1.3	Stochastic Gradient Descent		
	1.4	Building a Machine Learning Algorithm		
	1.5	Challenges Motivating Deep Learning		
2	<b>Fundamentals of Deep Networks</b>		<b>08</b>	<b>CO2</b>
	2.1	Common Architectural Principles of Deep Networks		
	2.2	Deep Feedforward Networks – Example of Ex OR		
	2.3	Gradient-Based Learning		
	2.4	Hidden Units, Architecture Design		
3	<b>Regularization and Optimization for Training Deep Models</b>		<b>12</b>	<b>CO2</b>
	3.1	Parameter Norm Penalties, Norm Penalties as Constrained Optimization, Regularization and Under-Constrained Problems, Dataset Augmentation, Noise Robustness		
	3.2	Semi-Supervised Learning, Multi-Task Learning, Early Stopping, Parameter Tying and Parameter Sharing , Sparse Representations Bagging and Other Ensemble Methods, Dropout, Adversarial Training, Tangent Distance, Tangent Prop, and Manifold Tangent Classifier		
	3.3	Challenges in Neural Network Optimization, Basic Algorithms		
	3.4	Parameter Initialization Strategies, Algorithms with Adaptive Learning Rates, Approximate Second-Order Methods Optimization Strategies and Meta-Algorithms		
4	<b>• Convolutional Networks</b>		<b>08</b>	<b>CO3</b>
	4.1	The Convolution Operation, Motivation, Pooling, Convolution and Pooling as an Infinitely Strong Prior		
	4.2	Variants of the Basic Convolution Function, Structured Outputs, Data Types		
	4.3	Efficient Convolution Algorithms, Random or Unsupervised Features, The Neuroscientific Basis for Convolutional Networks		
	4.4	Convolutional Networks and the History of Deep Learning		

<b>5</b>	<b>Sequence Modeling: Recurrent and Recursive Nets</b>		<b>07</b>	<b>CO3</b>
	<b>5.1</b>	Unfolding Computational Graphs, Recurrent Neural Networks, Bidirectional RNNs, Encoder-Decoder Sequence-to-Sequence Architectures		
	<b>5.2</b>	<ul style="list-style-type: none"> <li>Deep Recurrent Networks, Recursive Neural Networks, The Challenge of Long-Term Dependencies, Echo State Networks, Leaky Units and Other Strategies for Multiple Time Scales</li> </ul>		
	<b>5.3</b>	<ul style="list-style-type: none"> <li>The Long Short-Term Memory and Other Gated RNNs, Optimization for Long-Term Dependencies, Explicit Memory</li> </ul>		
<b>Total</b>			<b>45</b>	

**Recommended Books:**

<b>Sr. No.</b>	<b>Name/s of Author/s</b>	<b>Title of Book</b>	<b>Name of Publisher with country</b>	<b>Edition and Year of Publication</b>
1.	Josh Patterson and Adam Gibson	<i>Deep Learning A Practitioner's Approach</i>	O'Reilly Media	2017
2.	Nikhil Buduma	<i>Fundamentals of Deep Learning Designing Next-Generation Machine Intelligence Algorithms</i>	O'Reilly Media	2017
3.	Ian Goodfellow Yoshua Bengio Aaron Courville	<i>Deep Learning</i>	MIT Press	2017

- Instructor needs to provide additional resources to students for in-depth understanding and practical applicability of the indicated topic/topics.

Course Code	Course Title							
116h66L601	Deep Learning Laboratory							
	TH		P		TUT		Total	
Teaching Scheme(Hrs.)	-		02		-		02	
Credits Assigned	-		01		-		01	
Examination Scheme	Marks							
	CA		ESE	TW	O	P	P&O	Total
	ISE	IA						
	-	-	-	25	25	-	-	50

- Term-Work will consist of practical performance during the lab sessions covering the syllabus of “Deep Learning”, Students will be graded based on continuous assessment of their term work.
- Oral Examination will be based on laboratory work and the entire syllabus of “Deep Learning”.

Course Code	Course Title							
116h66C701	Natural Language Processing							
	TH			P		TUT		Total
Teaching Scheme(Hrs.)	03			-		-		03
Credits Assigned	03			-		-		03
Examination Scheme	Marks							
	CA		ESE	TW	O	P	P&O	Total
	ISE	IA						
	30	20						

**Course prerequisites:** Knowledge of Neural Networks

**Course Objectives:**

This course provides an introduction to the field of computational linguistics, aka natural language processing (NLP). It will cover fundamental as sounds, words, sentences, meanings, and conversations in context with NLP. Along with Linguistics as morphology, syntax, semantics it also touches upon application of deep learning for NLP.

**Course Outcomes:**

**At the end of successful completion of the course the student will be able to**

- CO1: Understand fundamentals of NLP
- CO2: Comprehend Words and Word Forms in NLP
- CO3: Establish concept of Structure and Semantics
- CO4: Applying Deep learning algorithm for NLP



<b>Module No.</b>	<b>Unit No.</b>	<b>Details</b>	<b>Hrs</b>	<b>CO</b>
<b>1</b>	<b>Basics of NLP</b>		<b>10</b>	<b>CO1</b>
	<b>1.1</b>	Biology of Speech Processing; Place and Manner of Articulation		
	<b>1.2</b>	Word Boundary Detection		
	<b>1.3</b>	Argmax based computations		
	<b>1.4</b>	HMM and Speech Recognition		
<b>2</b>	<b>Words and Word Forms</b>		<b>10</b>	<b>CO2</b>
	<b>2.1</b>	Morphology fundamentals; Morphological Diversity of Indian Languages		
	<b>2.2</b>	Morphology Paradigms, Finite State Machine Based Morphology, Automatic Morphology Learning		
	<b>2.3</b>	Shallow Parsing, Named Entities, Maximum Entropy Models, Random Fields		
<b>3.</b>	<b>Structures</b>		<b>10</b>	<b>CO3</b>
	<b>3.1</b>	Theories of Parsing, Parsing Algorithms		
	<b>3.2</b>	Robust and Scalable Parsing on Noisy Text as in Web documents		
	<b>3.3</b>	Hybrid of Rule Based and Probabilistic Parsing, Scope Ambiguity and Attachment Ambiguity resolution		
<b>4</b>	<b>Semantics</b>		<b>08</b>	<b>CO3</b>
	<b>4.1</b>	Lexical Knowledge Networks, Wordnet Theory		
	<b>4.2</b>	Indian Language Wordnets and Multilingual Dictionaries		
	<b>4.3</b>	Semantic Roles, Word Sense Disambiguation, WSD and Multilinguality, Metaphors, Coreference		
<b>5</b>	<b>NLP using Deep learning</b>		<b>07</b>	<b>CO4</b>
	<b>5.1</b>	Natural Language Processing and Recurrent Neural Networks, RNNs Mechanism		
	<b>5.2</b>	• Training RNNs, Meta Meaning of Hidden State of RNN, Tuning RNNs, Long Short-Term Memory Networks		
	<b>5.3</b>	• Sequence-to-Sequence Models, Advanced Sequence-to-Sequence Models, Sequence-to-Sequence Use Case		
<b>Total</b>			<b>45</b>	

**Recommended Books:**

<b>Sr. No.</b>	<b>Name/s of Author/s</b>	<b>Title of Book</b>	<b>Name of Publisher with country</b>	<b>Edition and Year of Publication</b>
1.	Allen, James	<i>Natural Language Understanding</i>	Benjamin/Cummings,	Second Edition, 1995
2.	Palash Goyal, Karan Jain, Sumit Pandey	<i>Deep Learning for Natural Language Processing: Creating Neural Networks with Python</i>	Apress	2018
3.	Jurafsky, Dan and Martin, James	<i>Speech and Language Processing</i>	Prentice Hall	2008
4.	Charniack, Eugene	<i>Statistical Language Learning</i>	MIT Press	1993

- Instructor needs to provide additional resources to students for in-depth understanding and practical applicability of the indicated topic/topics.

Course Code	Course Title							
116h66L701	Natural Language Processing Laboratory							
	TH		P		TUT		Total	
Teaching Scheme(Hrs.)	-		02		-		02	
Credits Assigned	-		01		-		01	
Examination Scheme	Marks							
	CA		ESE	TW	O	P	P&O	Total
	ISE	IA						
	-	-	-	25	25	-	-	50

- Term-Work will consist of practical performance during the lab sessions covering the syllabus of “Natural Language Processing”, Students will be graded based on continuous assessment of their term work.
- Oral Examination will be based on laboratory work and the syllabus of “Natural Language Processing”.