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BT: L1, L2				
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classification, error analysis, mutu label classification,	
(T?- Chanter ? and ?)	
Module - 3 Training Models: Linear regression, gradient descent, polynomial regression, learning curves,	10
Training Models: Linear regression, gradient descent, posture	
regularized linear models, logistic regression Support Vector Machine: linear, Nonlinear, SVM regression and under the hood	
(T2: Chapter 4 and 5)	
RBT: L1, L2	
Modulo 4	10
Decision Trees Training and Visualizing DT, making prediction, estimating class, the CART training, computational complexity, GINI impurity, Entropy, regularization Hyper parameters, Regression,	
instability	
Ensemble learning and Random Forest: Voting classifiers, Bagging and pasting, Random patches, Random forests, Boosting, stacking	
(T2: Chapter 6 and 7)	
RBT: L1, L2	
Module - 5 Maximum Likelihood - Minimum Description Length	10
Module - 5 Bayes Theorem - Concept Learning - Maximum Likelihood - Minimum Description Length Bayes Theorem - Concept Learning - Maximum Likelihood - Minimum Description Length Principle - Bayes Optimal Classifier - Gibbs Algorithm - Naïve Bayes Classifier - example-	
Principle – Bayes Optimal Classifier Bayesian Belief Network – EM Algorithm	
Bayesian Bellet Network - Environmental Bayesian Bayesian Bellet Network - Environmental Bayesian Bayes	
Text book (T1: Chapter 6)	
RBT: L1, L2	

For any problem calculated make cure that the application should have five an more

tables indicative areas include; health care, salary management, office automation, etc.

Laboratory Outcomes: The student should be able to:

- Create, Update and query on the database.
- Demonstrate the working of different concepts of DBMS
- Implement. analyze and evaluate the project developed for an application.

Conduct of Denotical Evamination

- For laboratories having only one part: Students are allowed to pick one experiment from Experiment distribution
 - For laboratories having PART A and PART B: Students are allowed to pick one experiment from PART A and one experiment from PART B, with equal opportunity.
- Change of experiment is allowed only once and marks allotted for procedure to be made zero of the changed part only.
 - on company part and the second of the second of the continues of the material of the second of the s k) For laboratories having only one part – Procedure + Execution + Viva-Voce: 15+70+15 = 100 Marks
 - l) For laboratories having PART A and PART B
 - i. Part A Procedure + Execution + Viva = 6 + 28 + 6 = 40 Marks
 - ii. Part B Procedure + Execution + Viva = 9 + 42 + 9 = 60 Marks

Separtment Dept. of Artificial Intelligence & Machine Learning Alva's Institute of Engineering and Technology Shobhavana Campus, Mijar Moodubidire 574 225, D.K. Kamataka, India