

# **SRM** Institute of Science and Technology

### **School of Computing**

#### DEPARTMENT OF DATA SCIENCE AND BUSINESS SYSTEMS

SRM Nagar, Kattankulathur – 603203, Chengalpattu District, Tamilnadu Academic Year: 2024-25 (ODD)

Test: CLAT-1[Portion: UNIT 1 & First half of 2nd Unit]Date: 23.02.2024Course Code & Title: 21CSE426T & Financial Machine LearningDuration: 100 MinutesYear & Sem: III Year & VI SemMax. Marks: 40

## Part A [ Answer all / 10 \* 1 = 10 Marks]

<ul><li>a. Features</li><li>b. coefficients c. Hyperparameters d. relations</li><li>2. Finding the best combination of hyperparameters of a model:</li></ul>			_			_		
<ul> <li>information and overall model performance.</li> <li>a. Features b. coefficients c. Hyperparameters d. relations</li> <li>2. Finding the best combination of hyperparameters of a model:  a. RMSE b. Model tuning c. Search d. SSE</li> <li>3. Finding the best combination of hyperparameters of a model:  a. RMSE b. Model tuning c. Search d. SSE</li> <li>4. The number of hidden nodes in each layer of ANN is of input layer &amp; output layer size a. sum b. difference c. mean d. square</li> <li>5. The cost function of OLS is a. RSS b. RMSE c. SSE d. MSE</li> <li>6. The dataset to be used in Linear Regression should not have :  a. multicollinearity b. multilinearity c. multigrid d. multisearch</li> <li>7. CostFunction = RSS + λ * Σ * [β   β   This is the formula that represents regularization a. Lasso b. Rigid c. Elastic net d. Elastic grid</li> <li>8 the coefficients lead to a lower variance and a lower error value.  a. Zeroing b. Shrinking c. Expanding d. Changing</li> <li>9. logistic regression models the of the output classes a. values b. labels c. Probabilitiesd. coefficients</li> <li>10. Using kernels, the original data is projected into a to classify the data better.</li> </ul>	1.	Dimensionality reduction is the process of reducing the				in a dataset	in a dataset while preserving	
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#### Part B [ Answer any 2/3 \* 15 = 30 marks]

- 1. You are tasked with designing a simple ANN to predict whether a patient has a particular disease based on various health metrics (e.g., blood pressure, cholesterol level, age). Explain the following:
  - The architecture of the ANN, including the choice of activation functions and the number of layers.
  - Write a Python code snippet using **TensorFlow/Keras** to create and compile this ANN model.
  - Describe the steps involved in training this model on a dataset and how you would evaluate its performance.
- 2. You are provided with a dataset containing information about different types of fruits (e.g., apples, oranges, bananas). You need to classify the fruits based on their physical characteristics such as weight, color, and size.
  - Explain the concept of the kernel trick in SVM and its importance in non-linear classification.
  - Write a Python code snippet using **sklearn** to implement the classifier with an RBF kernel for this task.
  - Outline the steps to perform data preprocessing, feature scaling, and model evaluation.
- 3. You are working on a binary classification problem where you need to predict whether a customer will buy a product based on their demographic information (e.g., age, income, location).
  - Explain the concept of the logistic function and its role in logistic regression.
  - Write a Python code snippet using **sklearn** to implement logistic regression for this classification
  - Discuss the steps involved in feature selection, model training, and interpreting the output coefficients.