

| USN | 1 | В | Y |  |  |  |  |  |  |  |  |
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# BMS INSTITUTE OF TECHNOLOGY AND MANAGEMENT

(An Autonomous Institute affiliated to Visvesvaraya Technological University, Belagavi) **SEMESTER END EXAMINATION QUESTION PAPER** 

#### **Second Semester MCA Degree Examination**

Regular / Make-up / Arrears / Supplementary

#### **BIG DATA ANALYTICS**

Time: 3 hrs.

Max. Marks: 100

Note: 1. Answer FIVE full questions, choosing ONE full question from each module.

| Q.<br>No | Module - 1   | Marks | CO & RBT |
|----------|--|-------|----------|
| 1a.      | What are Outliers and discuss causes of outliers   | 6     | CO1, K2  |
| b.       | What is Big Data? Demonstrate the working of analytical processing Model.  | 10    | CO1, K2  |
| c.       | Explain the different sources of Big data and Explain?   | 4     | CO1, K2  |
|          | OR   |       |          |
| 2a.      | Define Big Data and Characterise 5V's of Big Data.   | 10    | CO1, K2  |
| b.       | Construct Box plot for given data: 51,17,25,39,7,49,67,41,20,2,43,13.  | 4     | CO1, K2  |
| C.       | Explain the schemes to deal with missing values in a dataset.  | 6     | CO1, K2  |
|          | Module – 2   |       |          |
| 3a.      | Discuss the logistic regression role in predictive analytics.  | 7     | CO2, K2  |
| b.       | Justify the need of having support vector machines for predictive analytics.   | 7     | CO2, K2  |
| c.       | Differentiate the following  i) predictive analytics and descriptive analytics.  ii) hierarchical and non-hierarchical clustering. | 6     | CO2, K2  |
|          | OR   |       |          |
| 4a.      | Discuss various performance methods to evaluate classification models.   | 8     | CO2, K2  |
| b.       | Describe the role of decision trees in predictive analytics.   | 7     | CO2, K2  |
| c.       | Describe bagging and boosting concepts in predictive analytics.  | 5 /   | CO2, K2  |
|          | Module – 3   |       |          |
| 5a.      | Demonstrate core architecture of Hadoop with suitable block diagram. Discuss role of each component in detail.                     | 10    | CO3, K2  |
| b.       | Demonstrate different stages of MapReduce with an example.   | 10    | CO3, K2  |
|          | OR   | ii .  |          |

| 6a.  | Analyse the anatomy of writing data into a file in HDFS with a neat diagram.  |    | CO3, K2 |
|------|---|----|---------|
| b.   | Describe the role of combiner functions in MapReduce processing.  | 10 | CO3, K2 |
|      | Module – 4  |    | 7       |
| 7a.  | Discuss the architecture of Spark and Spark's language APIs.  | 10 | CO4, K2 |
| b.   | Discuss the dataframes and datasets in Spark.   | 10 | CO4, K2 |
|      | OR  |    |         |
| 8a.  | Elaborate on Spark's toolset with a neat sketch.  | 10 | CO4, K2 |
| b.   | Bring out the importance of lazy evaluations in Spark.  | 5  | CO4, K2 |
| C.   | Discuss the overview of structured API.   | 5  | CO4, K2 |
|      | Module – 5  |    |         |
| 9a.  | Analyze architecture of APACHE HIVE.  Explain different ways of inserting/loading data to HIVE tables with example.   | 10 | CO5, K2 |
| b.   | Illustrate HiveQL Data definition and Data manipulation commands with example.  | 10 | CO5, K2 |
|      | OR  |    |         |
| 10a. | Summarize various data types supported by HiveQL with an example.   | 8  | CO5, K2 |
| b.   | Design the hive solution for the following queries in HiveQL. Creating student table with USN, name of the student, year of join(yoj) ,course, email address, phone number and CGPA  i) Find the total no of students in each course. ii) List the student who is having maximum and minimum CGPA iii) Create a view to store the details of the students whose CGPA is greater than the 9.00. iv) List the students in the ascending order of their course | 8  | CO5, K2 |
| c.   | Illustrate Metastore in HIVE.   | 4  | CO5, K2 |

#### Course Outcomes (COs): At the end of the course, the student will be able to

| COs     | Statements   |
|---------|--|
| CO-1    | Identify the business problem for a given context and frame the objectives to solve it using data analytics tools. |
| CO-2    | Differentiate various types of analytics algorithms and context of their application.                              |
| CO-3    | Illustrate the architecture of HDFS and MapReduce.   |
| CO-4    | Explore Spark architecture and its language APIs.  |
| CO-5    | Write Hive queries against large datasets on clusters.   |
| K1- Rem | embering K2 - Understanding K3 – Applying K4- Analyzing K5 - Evaluating K6 - Creating                              |

"Success is the progressive realization of a worthy goal."

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| Q. No       | Scheme and   | Marks |
|-------------|--|-------|
| a)          | Solutions Brief description of outliers Types of outliers Causes of outliers   | 3 1   |
|             | • Data entry errors (human errors) • Measurement errors (instrument errors) • Experimental errors (data extraction or experiment planning/executing errors) • Intentional (dummy outliers made to test detection methods) • Data processing errors (data manipulation or data set unintended mutations) • Sampling errors (extracting or mixing data from wrong or various sources) • Natural (not an error, novelties in data)  | 2     |
| b)          | Big Data Definition with examples  | 2     |
|             | Dumps of Operational Data  Dum Gransformation  Conference of the Chambra of C | - 3   |
| E           | Explanation of each component Business understandings, data exploration, data preparation, data processing, lata analytics, data evaluation  | 5     |
| S<br>T<br>T | Social Networks provide human-sourced information from:  Craditional Business Systems  These organizations offer customers services or products  Machine Data  Social Networks  Local Data  Transaction Data  Machine Data   | 4     |
| 29) B       | olume, Velocity, Variety, Veracity, Validity, Vulnerability, Vulnerability   | 2*5   |
|             | Chart Title Value Variability  |       |
|             | Chart Title Value Variability Explanation of any 5   |       |
|             | 20   |       |
| (d)         | 0 1 2 3 4 5 6 7 8 9 10 11 12 12 15 6 7 8 9 10 11 12 15 16 17 8 9 10 11 12 15 16 17 8 9 10 11 12 15 16 16 16 16 16 16 16 16 16 16 16 16 16  | 4M    |
|             | lethods to treat missing values — Repare Delete, Keep - 2Mean eletion, Mean/ Mode/ Median Imputation, Prediction Model KNN Imputation with amples  | 6 M   |

| Q.<br>Vo |  | Scheme and Solutions   |  | Marks |
|----------|--|--|--|-------|
| 1)       | Explanation & examples Logistic regression aims to mover variable and one or more incompleted and techniques falling in limited cate techniques have recently experimental machine Learning, as this is on aren't limited to specific industrial analytics technique compared to the Explanation & examples Non-linear SVM means that the a straight line. The benefit is between your datapoints without  | easure the relationship between a dependent variables (usually continuous scores. A categorical variable is a regories instead of being continuous rienced a surge in demand due to the of the most commonly used algorithm calculations of the most commonly used algorithm and the common of the most commonly used algorithm and the common of the most common o | categorical dependent<br>nuous) by plotting the<br>a variable that can take<br>bus.Logistic regression<br>of the increasing use of<br>orithms. Its applications<br>monly used and flexible | 5+2   |
| ,        | Descriptive Analytics  | Predictive Analytics   | ٦  |       |
|          | tells you what happened in the past These are generally pre-cannel reports, dashboards and MIS operational reports etc. E.g. Profit per store, per region Sales through various channels is the branch of the advanced analytics which is used to make predictions about unknown future events.  is generally used to produce correlation, cross tabulation frequency etcetera. These techniques are determined to find the regularities in the data and to reveal patterns. The other application of descriptive analysis is to discover the captivating subgroups in the major part of the data. | happen in 'future'. This needs larger data set expertise and tool set. e.g.: Which channels are likely to perform better in next quarter based on past data.  is a preliminary stage of data processing that creates a summary of historical data to yield useful information.  The primary objective of predictive analysis is to predict future results instead of current behaviour. It involves the supervised learning functions used for the   |  |       |
|          | Hierarchical Hierarchical Clustering involves creating clusters in a predefined order from top to bottom.  | Non-hierarchical  Non Hierarchical Clustering involves formation of new clusters by merging or splitting the clusters instead of following a hierarchical order.   | 3 M  |       |
|          | t is considered less reliable<br>than Non Hierarchical   | It is comparatively more reliable than Hierarchical  | e 9  |       |

| Clustering   | Clustering.   |
|--|---|
| It is considered slower than Non Hierarchical Clustering. It is very problematic to apply this technique where and | It is comparatively more faster than Hierarchical Clustering.  It can work better then  |
| this technique when we have data with high level of error.  Performance Evaluation Measure                         | Hierarchical clustering even when error is there.   |
| <ul><li>Confusion Matrix</li><li>Precision</li><li>Recall/ Sensitivity</li></ul>                                   | Expl. of ans 4-2meal  |
| <ul><li>Specificity</li><li>F1-Score</li><li>AUC &amp; ROC Curve with</li></ul>                                    | examples 3-14   |
| is to split a population of data in  |   |
| Root trade → → With Friends?   | Splitting Splitting   |
| Yes No   | Decision Node   |
| Yes/ No Walk/ Above par Cold? Above par  | Walk or card?  /Cart  Cold?   |
| Yes / No Yes Above Below Below par par Leaf Nod  | Above par   |
| of the original data. Boosting is abbservation based on the last class   | e variance in the prediction by generating additional and combinations with repetitions to produce multi-sets an iterative technique which adjusts the weight of an sification. If an observation was classified incorrectly, f this observation. Boosting in general builds strong |
| Advantages:  Reduces over-fitting of the   | e model.  |
| <ul> <li>Handles higher dimensiona</li> <li>Maintains accuracy for mis</li> </ul> <b>Pisadvantages:</b>            | ssing data.   |
| coosting is used to create a college   | ection of predictors. In this technique learners are  |
| owned comment II !!  | learners fitting simple models to the data and then   |

step, the goal is to improve the accuracy from the prior tree. When an input is misclassified by a hypothesis, its weight is increased so that next hypothesis is more

P8\_3

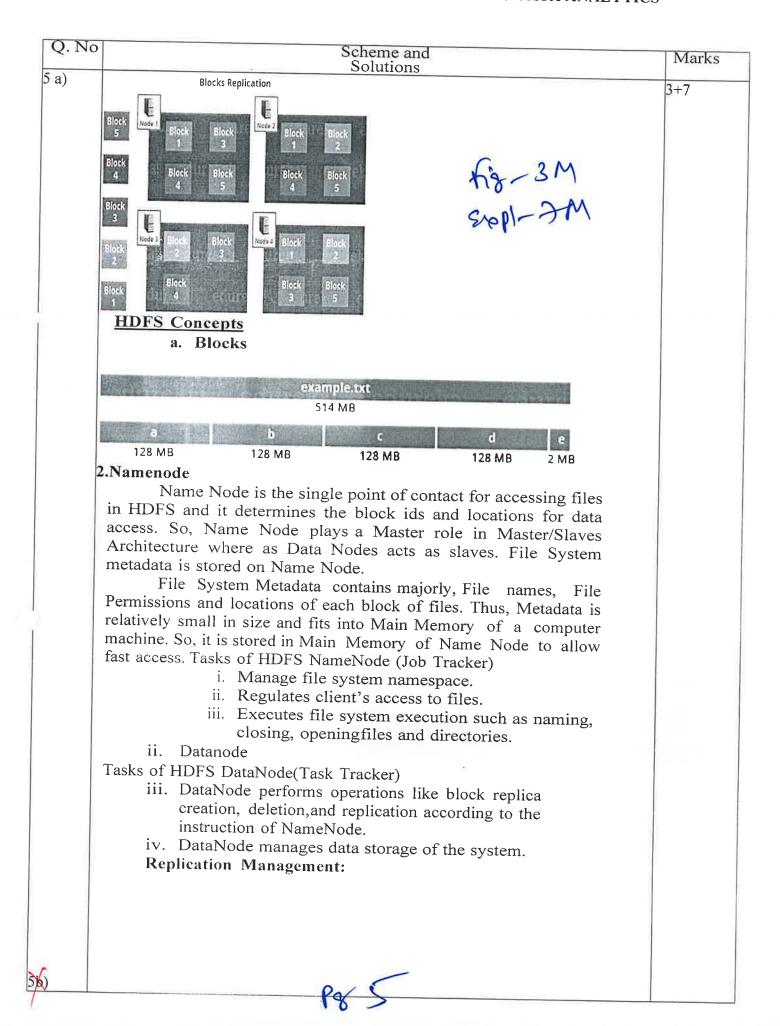
likely to classify it correctly. This process converts weak learners into better performing model.

Advantages:

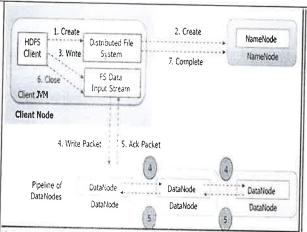
- Supports different loss function (we have used 'binary:logistic' for this example).
- Works well with interactions.

Disadvantages:

- Prone to over-fitting.
- Requires careful tuning of different hyper-parameters.



6a)



F8-3M ENAN. of Stape-3M

3+7

The client creates the file by calling create() method on Step 1: DistributedFileSystem. Step 2: DistributedFileSystem makes an RPC call to the namenode to create a new file in the filesystem's namespace, with no blocks associated with it. The namenode performs various checks to make sure the file doesn't already exist and that the client has the right permissions to create the file. If these checks pass, the namenode makes a record of the new file; otherwise, file creation fails and the client is thrown an IOException. TheDistributedFileSystem returns an FSDataOutputStream for the client to start writing data to. Step 3: As the client writes data, DFSOutputStream splits it into packets, which it writes to an internal queue, called the data queue. The data queue is consumed by the DataStreamer, which is responsible for asking the namenode to allocate new blocks by picking a list of suitable datanodes to store the replicas. The list of datanodes forms a pipeline, and here we'll assume the replication level is three, so there are three nodes in the pipeline. TheDataStreamer streams the packets to the first datanode in the pipeline, which stores the packet and forwards it to the second datanode in the pipeline. Step 4: Similarly, the second datanode stores the packet and forwards it to the third (and last) datanode in the pipeline. Step 5: DFSOutputStream also maintains an internal queue of packets that are waiting to be acknowledged by datanodes, called the ack queue. A packet is removed from the ack queue only when it has been acknowledged by all the datanodes in the pipeline. Step 6: When the client has finished writing data, it calls close() on the stream.

5 a)

# Sample code Map Redule

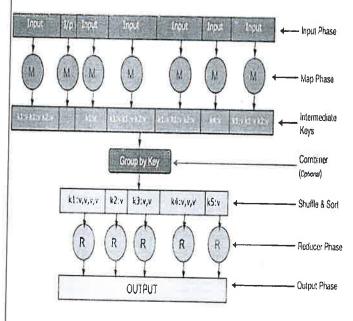
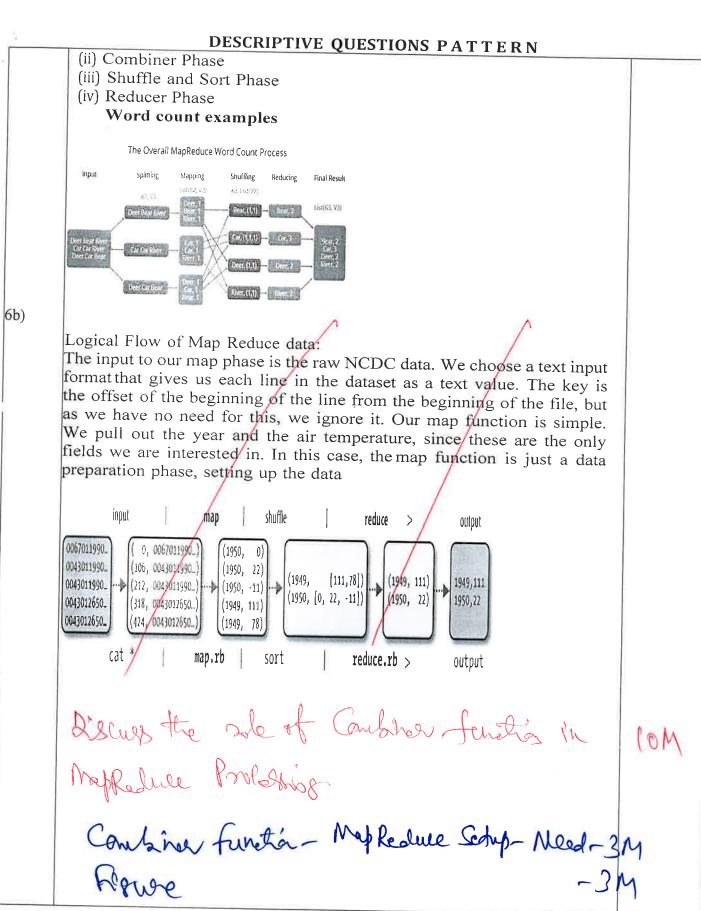


Fig-4M Sopl-2M Example-4M

(i)Map Phase



Explanation with assume

-4M

| Q. No | Scheme and Solutions  | Marks          |
|-------|---|----------------|
| 7 a)  | Driver Program  Driver Program  Spark Context  Cluster Manager  Worker node Executor  Worker node Executor  Task  |                |
|       | Spark has integration with a variety of programming languages such as Scala, Java, Python, and R. Developers can write their Spark program in either of these languages. This freedom of language is also one of the reasons why Spark is popular among developers. If we compare this to Hadoop MapReduce, in MapReduce, the developers had only one choice: Java, which made it difficult for developers from another programming languages to work on MapReduce.  Significance of dataframe, Features of dataframe Creating dataframe Dataframe operations Applications of dataframe |                |
| 8 a)  | Structured Advanced Analytics Libraries & Ecosystem FA-3M  Structured APIS  Datasets DataFrames SQL   |                |
| b)    | Low-level APIs  RDDs Distributed Variables  lazy Cultuatian  inark Transformation is a function that made   | CM             |
| 1     | <b>Spark Transformation</b> is a function that produces new RDD from the existing RDDs, at takes RDD as input and produces one or more RDD as output. Each time it creates new RDD when we apply any transformation. Thus, the so input RDDs, cannot be changed since RDD are imputable in nature.  With features   | 2=2            |
|       | Three types of structured API Dataframe, Dataset . SQL tables with examples  2/2 M each   | <del>5</del> M |

