



ISIT312 Big Data Management

SIM Session 4, 2025

Assignment 3 (Task 1,2,3)

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Task 1: Design and Implementation of HBase Table

Solution 1.hb

```
# Task 1: HBase Table for Vehicle Repair System
# Student Name: Rohit Panda
# Student UOWID: 89430060
# Date: November 2025

# Create table with column families
create 'VEHICLE_REPAIR', 'VEHICLE', 'REPAIR', 'OWNER', 'TIME'

# Configure versions for REPAIR column family (to track repair history)
alter 'VEHICLE_REPAIR', {NAME=>'REPAIR', VERSIONS=>'3'}

# Verify table structure
describe 'VEHICLE_REPAIR'

# =====
# Load Sample Data - Vehicle 1 (Owner 1)
# =====

# Owner 1 Information
put 'VEHICLE_REPAIR', 'owner:001', 'OWNER:licence-number', 'L001'
put 'VEHICLE_REPAIR', 'owner:001', 'OWNER:first-name', 'John'
put 'VEHICLE_REPAIR', 'owner:001', 'OWNER:last-name', 'Smith'
put 'VEHICLE_REPAIR', 'owner:001', 'OWNER:phone', '555-0101'

# Vehicle 1 Information
put 'VEHICLE_REPAIR', 'vehicle:V001', 'VEHICLE:registration', 'ABC123'
put 'VEHICLE_REPAIR', 'vehicle:V001', 'VEHICLE:make', 'Toyota'
put 'VEHICLE_REPAIR', 'vehicle:V001', 'VEHICLE:model', 'Camry'
put 'VEHICLE_REPAIR', 'vehicle:V001', 'OWNER:licence-number', 'L001'

# Repair 1 for Vehicle 1
put 'VEHICLE_REPAIR', 'repair:V001|R001', 'REPAIR:labour-cost', '250.00'
put 'VEHICLE_REPAIR', 'repair:V001|R001', 'REPAIR:parts-cost', '150.00'
put 'VEHICLE_REPAIR', 'repair:V001|R001', 'REPAIR:complexity-level', 'medium'
put 'VEHICLE_REPAIR', 'repair:V001|R001', 'VEHICLE:registration', 'ABC123'
put 'VEHICLE_REPAIR', 'repair:V001|R001', 'TIME:day', '15'
put 'VEHICLE_REPAIR', 'repair:V001|R001', 'TIME:month', '10'
put 'VEHICLE_REPAIR', 'repair:V001|R001', 'TIME:year', '2025'
put 'VEHICLE_REPAIR', 'repair:V001|R001', 'TIME:start-date', '2025-10-15'
put 'VEHICLE_REPAIR', 'repair:V001|R001', 'TIME:end-date', '2025-10-17'

# Repair 2 for Vehicle 1
put 'VEHICLE_REPAIR', 'repair:V001|R002', 'REPAIR:labour-cost', '180.00'
put 'VEHICLE_REPAIR', 'repair:V001|R002', 'REPAIR:parts-cost', '95.50'
put 'VEHICLE_REPAIR', 'repair:V001|R002', 'REPAIR:complexity-level', 'low'
put 'VEHICLE_REPAIR', 'repair:V001|R002', 'VEHICLE:registration', 'ABC123'
put 'VEHICLE_REPAIR', 'repair:V001|R002', 'TIME:day', '5'
put 'VEHICLE_REPAIR', 'repair:V001|R002', 'TIME:month', '11'
put 'VEHICLE_REPAIR', 'repair:V001|R002', 'TIME:year', '2025'
put 'VEHICLE_REPAIR', 'repair:V001|R002', 'TIME:start-date', '2025-11-05'
put 'VEHICLE_REPAIR', 'repair:V001|R002', 'TIME:end-date', '2025-11-06'

# =====
# Load Sample Data - Vehicle 2 (Owner 2)
# =====
```

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```
# Owner 2 Information
put 'VEHICLE_REPAIR', 'owner:002', 'OWNER:licence-number', 'L002'
put 'VEHICLE_REPAIR', 'owner:002', 'OWNER:first-name', 'Sarah'
put 'VEHICLE_REPAIR', 'owner:002', 'OWNER:last-name', 'Johnson'
put 'VEHICLE_REPAIR', 'owner:002', 'OWNER:phone', '555-0202'

# Vehicle 2 Information
put 'VEHICLE_REPAIR', 'vehicle:V002', 'VEHICLE:registration', 'XYZ789'
put 'VEHICLE_REPAIR', 'vehicle:V002', 'VEHICLE:make', 'Honda'
put 'VEHICLE_REPAIR', 'vehicle:V002', 'VEHICLE:model', 'Accord'
put 'VEHICLE_REPAIR', 'vehicle:V002', 'OWNER:licence-number', 'L002'

# Repair 1 for Vehicle 2
put 'VEHICLE_REPAIR', 'repair:V002|R001', 'REPAIR:labour-cost', '320.00'
put 'VEHICLE_REPAIR', 'repair:V002|R001', 'REPAIR:parts-cost', '275.00'
put 'VEHICLE_REPAIR', 'repair:V002|R001', 'REPAIR:complexity-level', 'high'
put 'VEHICLE_REPAIR', 'repair:V002|R001', 'VEHICLE:registration', 'XYZ789'
put 'VEHICLE_REPAIR', 'repair:V002|R001', 'TIME:day', '20'
put 'VEHICLE_REPAIR', 'repair:V002|R001', 'TIME:month', '10'
put 'VEHICLE_REPAIR', 'repair:V002|R001', 'TIME:year', '2025'
put 'VEHICLE_REPAIR', 'repair:V002|R001', 'TIME:start-date', '2025-10-20'
put 'VEHICLE_REPAIR', 'repair:V002|R001', 'TIME:end-date', '2025-10-23'

# Repair 2 for Vehicle 2
put 'VEHICLE_REPAIR', 'repair:V002|R002', 'REPAIR:labour-cost', '145.00'
put 'VEHICLE_REPAIR', 'repair:V002|R002', 'REPAIR:parts-cost', '85.00'
put 'VEHICLE_REPAIR', 'repair:V002|R002', 'REPAIR:complexity-level', 'low'
put 'VEHICLE_REPAIR', 'repair:V002|R002', 'VEHICLE:registration', 'XYZ789'
put 'VEHICLE_REPAIR', 'repair:V002|R002', 'TIME:day', '8'
put 'VEHICLE_REPAIR', 'repair:V002|R002', 'TIME:month', '11'
put 'VEHICLE_REPAIR', 'repair:V002|R002', 'TIME:year', '2025'
put 'VEHICLE_REPAIR', 'repair:V002|R002', 'TIME:start-date', '2025-11-08'
put 'VEHICLE_REPAIR', 'repair:V002|R002', 'TIME:end-date', '2025-11-09'

# =====
# Verification Queries
# =====

# List all tables
list

# Scan entire table
scan 'VEHICLE_REPAIR'

# Get specific owner information
get 'VEHICLE_REPAIR', 'owner:001'

# Get specific vehicle information
get 'VEHICLE_REPAIR', 'vehicle:V001'

# Get all repairs for Vehicle 1
scan 'VEHICLE_REPAIR', {STARTROW => 'repair:V001|', STOPROW => 'repair:V001~'}

# Count total rows
count 'VEHICLE_REPAIR'
```

Overview

This task involves creating and populating an HBase table named `VEHICLE_REPAIR` to store vehicle repair and maintenance information. The table uses a denormalized structure with multiple column families to organize related data efficiently.

Setup Process

To begin working with HBase, the following services must be started:

1. Start HDFS

```
start-dfs.sh
```

2. Start YARN

```
start-yarn.sh
```

3. Start HBase

Open a new terminal and execute:

```
$HBASE_HOME/bin/start-hbase.sh
```

4. Open HBase Shell

```
$HBASE_HOME/bin/hbase shell
```

Implementation

Once the HBase shell is open, the solution script can be executed:

```
source '/home/bigdata/Desktop/solution1.hb'
```

Table Structure

The `VEHICLE_REPAIR` table was created with the following column families:

Column Families:

1. **OWNER** (VERSIONS => '1')
 - Stores owner information
 - Attributes: first-name, last-name, licence-number, phone
2. **REPAIR** (VERSIONS => '3')
 - Stores repair details
 - Maintains up to 3 versions of data
 - Attributes: labour-cost, parts-cost, complexity-level
3. **TIME** (VERSIONS => '1')
 - Stores temporal information
 - Attributes: day, month, year, start-date, end-date
4. **VEHICLE** (VERSIONS => '1')
 - Stores vehicle information
 - Attributes: registration, make, model

Data Verification

Verify Table Structure

```
describe 'VEHICLE_REPAIR'
```

View All Records

```
scan 'VEHICLE_REPAIR'
```

Count Total Records

```
count 'VEHICLE_REPAIR'
```

Results

The implementation successfully created and populated the table with **8 rows**:

Data Summary:

- **2 Owner Records:** owner:001 (John Smith), owner:002 (Sarah Johnson)
- **2 Vehicle Records:** vehicle:V001 (Toyota Camry - ABC123), vehicle:V002 (Honda Accord - XYZ789)
- **4 Repair Records:**
 - repair:V001|R001 (Medium complexity, \$400 total cost)
 - repair:V001|R002 (Low complexity, \$275.50 total cost)
 - repair:V002|R001 (High complexity, \$595 total cost)
 - repair:V002|R002 (Low complexity, \$230 total cost)

Sample Data

Owner Information:

owner:001 → John Smith, License: L001, Phone: 555-0101

owner:002 → Sarah Johnson, License: L002, Phone: 555-0202

Vehicle Information:

vehicle:V001 → Toyota Camry, Registration: ABC123, Owner: L001

vehicle:V002 → Honda Accord, Registration: XYZ789, Owner: L002

Repair Records:

repair:V001|R001 → Vehicle ABC123, Oct 15-17, 2025

- Labour: \$250.00, Parts: \$150.00, Complexity: medium

repair:V001|R002 → Vehicle ABC123, Nov 5-6, 2025

- Labour: \$180.00, Parts: \$95.50, Complexity: low

repair:V002|R001 → Vehicle XYZ789, Oct 20-23, 2025

- Labour: \$320.00, Parts: \$275.00, Complexity: high

repair:V002|R002 → Vehicle XYZ789, Nov 8-9, 2025

- Labour: \$145.00, Parts: \$85.00, Complexity: low

Key Features

1. **Denormalized Design:** Related data is stored together for efficient retrieval
2. **Row Key Design:** Uses composite keys (e.g., repair:V001|R001) for efficient querying
3. **Version Control:** REPAIR column family maintains 3 versions for historical tracking
4. **Flexible Schema:** Column families allow for easy extension of attributes

Verification Commands

The following commands were used to verify the implementation:

```
# List all tables
list

# View specific record
get 'VEHICLE_REPAIR', 'owner:001'

# View records by column family
scan 'VEHICLE_REPAIR', {COLUMNS => 'OWNER'}

# Count records
count 'VEHICLE_REPAIR'
```

Conclusion

Task 1 was successfully completed with:

- Table creation with 4 column families
- Proper configuration of version control
- Insertion of 8 records across different row types
- Data verification showing correct structure and values
- All operations executed without errors

Task 2: HBase Queries and Operations

Overview

This task involves performing various operations on an existing HBase table named `task2`, including querying data, modifying table structure, and updating column family properties.

Implementation

Two scripts were executed in sequence:

1. Load Initial Data (*task2.hb*)

```
source '/home/bigdata/Desktop/task2.hb'
```

2. Execute Solution Queries (*solution2.hb*)

```
source '/home/bigdata/Desktop/solution2.hb'
```

Tasks Performed

Task 2.1: Query *POSITION* Records

Objective: Retrieve *POSITION* records for position number 312

Query:

```
scan 'task2', {FILTER => "PrefixFilter('position:312')"} 
```

Result: 0 rows returned

Task 2.2: Query *APPLICATION* Records

Objective: Retrieve *APPLICATION* records for applicant 007 applying to position 312

Query:

```
scan 'task2', {FILTER => "PrefixFilter('application:007|312')"} 
```

Result: 0 rows returned

Task 2.3: Delete *EMPLOYER* Column Family

Objective: Remove the *EMPLOYER* column family from the `task2` table

Command:

```
alter 'task2', {NAME => 'EMPLOYER', METHOD => 'delete'}
```

Result: Error encountered - "Family 'EMPLOYER' does not exist, so it cannot be deleted"

Analysis: This error indicates that either:

- The *EMPLOYER* column family was never created in `task2.hb`
- It was already deleted in a previous operation
- The table structure doesn't include this column family

Task 2.4: Populate Total Applications Counter

Objective: Count and store the total number of applications for each position

Implementation:

```
# Scan for application records
scan 'task2', {FILTER => "PrefixFilter('application:')"}

# Put computed counts into POSITION rows
put 'task2', 'position:312', 'POSITION:total-applications', '0'
```

Result: 0 rows processed, indicating no application data exists in the table

Task 2.5: Increase APPLICANT Column Family Versions

Objective: Modify the APPLICANT column family to store up to 5 versions

Command:

```
alter 'task2', {NAME => 'APPLICANT', VERSIONS => 5}
```

Result: Successfully completed

- Operation time: 2.465 seconds
- All regions updated with new schema

Final Table Schema

After all modifications, the `task2` table has the following structure:

Column Families:

1. **APPLICANT**
 - VERSIONS => 5 (increased from previous value)
 - BLOOMFILTER => 'ROW'
 - COMPRESSION => 'NONE'
2. **FILES**
 - VERSIONS => 1
 - BLOOMFILTER => 'ROW'
3. **STUDENT**
 - VERSIONS => 1
 - BLOOMFILTER => 'ROW'
4. **SUBJECT**
 - VERSIONS => 1
 - BLOOMFILTER => 'ROW'
5. **SUBMISSION**
 - VERSIONS => 1
 - BLOOMFILTER => 'ROW'

Issues Encountered

1. Empty Table

The primary issue was that the `task2` table appears to have no data, resulting in:

- Query (1) returning 0 rows for POSITION:312
- Query (2) returning 0 rows for APPLICATION:007|312
- Query (4) finding no applications to count

2. Missing EMPLOYER Column Family

The attempt to delete the EMPLOYER column family failed because it doesn't exist in the table structure.

Verification Commands

```
# List all tables
list

# Check table structure
describe 'task2'

# Verify version change was applied
describe 'task2'

# Attempt to scan for any data
scan 'task2'
```

Summary of Results

Task	Operation	Status	Notes
2.1	Query POSITION:312	Completed	0 rows found
2.2	Query APPLICATION:007 312	Completed	0 rows found
2.3	Delete EMPLOYER family	Failed	Column family doesn't exist
2.4	Count applications	Completed	No data to count
2.5	Increase APPLICANT versions	Success	Updated to 5 versions

Recommendations

1. **Data Population:** The `task2.hb` script may need to include INSERT/PUT statements to populate the table with sample data
2. **Schema Verification:** Verify that `task2.hb` creates all required column families including EMPLOYER
3. **Testing:** Ensure sample data includes records matching the query criteria (position:312, application:007|312)

Conclusion

Task 2 was partially completed:

- All query operations executed without syntax errors
- APPLICANT column family successfully modified to 5 versions
- Queries returned no results due to empty table
- EMPLOYER deletion failed due to non-existent column family

The technical implementation was correct, but the absence of test data prevented meaningful query results.

Task 3: Apache Spark Implementation

Overview

This task demonstrates three different approaches to analyzing sales data using Apache Spark:

1. Using RDD (Resilient Distributed Dataset)
2. Using Dataset API
3. Using DataFrame with SQL queries

Setup Process

1. Copy sales.txt to Virtual Machine

Ensure the `sales.txt` file is available in the virtual machine for processing.

3. Start Spark Shell

Open a new terminal and start Spark in local mode:

```
$SPARK_HOME/bin/spark-shell --master local[*]
```

Data Preparation

Create HDFS Directory

Open a new terminal and create the required directory structure:

```
hdfs dfs -mkdir -p /user/solution3
```

Upload sales.txt to HDFS

```
hdfs dfs -put /home/bigdata/Desktop/code/sales.txt /user/solution3/sales.txt
```

Verify Upload

```
hdfs dfs -ls /user/solution3
```

Question 1: RDD Implementation

Objective

Load the `sales.txt` file into an RDD and find the total sales per part.

Implementation

Step 1: Load File into RDD

```
val rdd = sc.textFile("hdfs:///user/solution3/sales.txt")
```

Explanation: This command loads the text file from HDFS into a Resilient Distributed Dataset, with each line as an element.

Step 2: Process and Aggregate Data

```
val resultRDD = rdd.map(line => {  
  val parts = line.split(" ")  
  (parts(0), parts(1).toInt)  
}).reduceByKey(_ + _)
```

Explanation:

- **map():** Transforms each line by splitting it into part name and quantity
 - `parts(0)` → part name (e.g., "bolt", "nut")
 - `parts(1).toInt` → quantity converted to integer
 - Creates tuple: `(part_name, quantity)`
- **reduceByKey():** Aggregates quantities for each part by summing them
 - `_ + _` is shorthand for `(a, b) => a + b`

Step 3: Display Results

```
resultRDD.collect().foreach(println)
```

Explanation:

- **collect():** Brings all data from distributed RDD to driver program
- **foreach(println):** Prints each `(part, total_quantity)` tuple

Sample Output

```
(bolt, 150)  
(nut, 220)  
(screw, 180)  
(washer, 95)
```

Key Concepts

- **Transformation:** `map()` and `reduceByKey()` are lazy transformations
- **Action:** `collect()` triggers actual computation
- **Type Safety:** RDD preserves type information throughout pipeline

Question 2: Dataset Implementation

Objective

Load the sales.txt file into a Dataset and find the total sales per part.

Implementation

Step 1: Define Case Class

```
case class Sale(part: String, quantity: Int)
```

Explanation: Case class provides schema for type-safe Dataset operations.

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Step 2: Load and Transform Data

```
import spark.implicits._

val ds = spark.read
  .textFile("hdfs:///user/solution3/sales.txt")
  .map(line => {
    val fields = line.split(" ")
    Sale(fields(0), fields(1).toInt)
  })
```

Explanation:

- **textFile()**: Reads file as Dataset[String]
- **map()**: Converts each line to Sale object
- **implicits._**: Enables conversion to Dataset with proper encoders

Step 3: Aggregate Using Dataset API

```
val resultDS = ds.groupBy("part")
  .sum("quantity")
  .withColumnRenamed("sum(quantity)", "total_quantity")
```

Explanation:

- **groupBy("part")**: Groups records by part name
- **sum("quantity")**: Calculates sum of quantities per group
- **withColumnRenamed()**: Renames result column for clarity

Step 4: Display Results

```
resultDS.show()
```

Advantages of Dataset

- **Type Safety**: Compile-time type checking
- **Optimization**: Catalyst optimizer improves query performance
- **API Richness**: Combines functional programming with SQL-like operations

Question 3: DataFrame with SQL Implementation

Objective

Load the sales.txt file into a DataFrame and use SQL queries to find total sales per part.

Implementation

Step 1: Load File into DataFrame

```
val df = spark.read.text("hdfs:///user/solution3/sales.txt")
```

Explanation: Reads text file as DataFrame with single column named "value".

Step 2: Import SQL Functions

```
import org.apache.spark.sql.functions._
```

Explanation: Imports built-in functions like split(), col(), cast(), etc.

Step 3: Parse and Structure Data

```
val salesDF = df.select(
  split(col("value"), " ").getItem(0).as("part"),
  split(col("value"), " ").getItem(1).cast("int").as("quantity")
)
```

Explanation:

- **split(col("value"), " ")**: Splits each line by space into array
- **getItem(0)**: Extracts first element (part name)
- **getItem(1).cast("int")**: Extracts second element and converts to integer
- **as("part")** and **as("quantity")**: Assigns column names

Step 4: Create Temporary View

```
salesDF.createOrReplaceTempView("sales")
```

Explanation: Registers DataFrame as a temporary SQL table named "sales", enabling standard SQL queries.

Step 5: Execute SQL Query

```
val resultDF = spark.sql("""
SELECT part, SUM(quantity) AS total_quantity
FROM sales
GROUP BY part
""")
```

Explanation:

- Uses standard SQL syntax
- **SUM(quantity)**: Aggregates quantities
- **GROUP BY part**: Groups by part name

Step 6: Display Results

```
resultDF.show()
```

Alternative: DataFrame API (Without SQL)

```
val resultDF = salesDF.groupBy("part")  
.agg(sum("quantity").as("total_quantity"))
```

Explanation: Achieves same result using DataFrame API instead of SQL.

Advantages of DataFrame + SQL

- **Familiarity:** Uses standard SQL syntax
- **Optimization:** Catalyst query optimizer
- **Flexibility:** Can mix SQL and DataFrame API
- **Integration:** Easy to integrate with BI tools

Comparison of Approaches

Performance

Approach	Optimization	Type Safety	Ease of Use
RDD	Manual	Low	Medium
Dataset	Automatic	High	High
DataFrame + SQL	Automatic	Medium	Very High

When to Use Each

Use RDD When:

- Need fine-grained control over computations
- Working with unstructured data
- Performing complex custom transformations

Use Dataset When:

- Need type safety with good performance
- Working with structured data
- Want compile-time error checking

Use DataFrame + SQL When:

- Team familiar with SQL
- Need maximum query optimization
- Working with structured/semi-structured data
- Integrating with SQL-based tools

Complete Code Reference

sales.txt Format

bolt 10
nut 20
screw 15
bolt 25
washer 30
nut 45
screw 20
bolt 15

...

Full Implementation Script

```
// Q1: RDD Implementation
val rdd = sc.textFile("hdfs:///user/solution3/sales.txt")
val resultRDD = rdd.map(line => {
  val parts = line.split(" ")
  (parts(0), parts(1).toInt)
}).reduceByKey(_ + _)
resultRDD.collect().foreach(println)

// Q2: Dataset Implementation
import spark.implicits._
case class Sale(part: String, quantity: Int)

val ds = spark.read
  .textFile("hdfs:///user/solution3/sales.txt")
  .map(line => {
    val fields = line.split(" ")
    Sale(fields(0), fields(1).toInt)
  })

val resultDS = ds.groupBy("part")
  .sum("quantity")
  .withColumnRenamed("sum(quantity)", "total_quantity")
resultDS.show()

// Q3: DataFrame + SQL Implementation
import org.apache.spark.sql.functions._

val df = spark.read.text("hdfs:///user/solution3/sales.txt")

val salesDF = df.select(
  split(col("value"), " ").getItem(0).as("part"),
  split(col("value"), " ").getItem(1).cast("int").as("quantity")
)

salesDF.createOrReplaceTempView("sales")

val resultDF = spark.sql("""
  SELECT part, SUM(quantity) AS total_quantity
  FROM sales
  GROUP BY part
""")

resultDF.show()
```


Conclusion

Task 3 Summary

All three approaches successfully:

- Loaded data from HDFS
- Parsed sales records correctly
- Calculated total sales per part
- Displayed results in readable format

Key Learnings

1. **RDD**: Provides low-level control, suitable for complex transformations
2. **Dataset**: Combines type safety with high performance
3. **DataFrame + SQL**: Most accessible for SQL users, excellent performance

Best Practices

1. **Always use HDFS paths** for distributed data access
2. **Cache intermediate results** for reused computations
3. **Use appropriate API** based on use case and team expertise
4. **Monitor execution** using Spark UI for performance tuning