

Assignment-3: Pig and Hive

- Keshav Chandak(IMT2021003)
- Sunny Kaushik(IMT2021007)
- Muteeb Sheikh(IMT2021008)
- Rishi Nelapati(IMT2021076)

Question-1

Overview

This part focuses on designing and implementing data pipelines using Hive to efficiently analyze and clean educational datasets. The datasets include:

- `Course_Attendance.csv`
- `Enrollment_Data.csv`
- `GradeRosterReport.csv`

The primary tasks include defining schemas, creating Hive tables, loading data, and performing data cleaning operations using HiveQL.

Folder Structure

- **Assignment_3_NoSQL_PiG_Hive.pdf**: The assignment document detailing the tasks and requirements.
 - **Course_Attendance.csv**: Contains raw data on course attendance.
 - **Enrollment_Data_v7.csv**: Cleaned and processed enrollment data.
 - **GradeRosterReport_v4.csv**: Cleaned and processed grade roster data.
 - **create_and_load_tables.hql**: HiveQL script to define schemas, create tables, and load raw data.
 - **data_cleaning.hql**: HiveQL script to clean and transform data.
 - **readme.md**: Part (a) documentation (this file).
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Steps and Scripts

1. Define Schemas and Create Tables

The `create_and_load_tables.hql` script defines the schema and creates Hive tables for each dataset:

Course Attendance Table

Schema:

- Course (STRING)
- Instructor (STRING)
- Name (STRING)

- Email_Id (STRING)
- Member_Id (STRING)
- Number_of_classes_attended (INT)
- Number_of_classes_absent (INT)
- Average_Attendance_Percentage (FLOAT)

Enrollment Data Table

Schema:

- Course_Type (STRING)
- Student_ID (STRING)
- Student_Name (STRING)
- Program (STRING)
- Batch (STRING)
- Period (STRING)
- Enrollment_Date (DATE)
- Primary_Faculty (STRING)
- Subject_Code_Name (STRING)
- Section (STRING)

Grade Roster Report Table

Schema:

- Academy_Location (STRING)
- Student_ID (STRING)
- Student_Status (STRING)
- Admission_ID (STRING)
- Admission_Status (STRING)
- Student_Name (STRING)
- Program_Name (STRING)
- Batch (STRING)
- Period (STRING)
- Subject_Code_Name (STRING)
- Section (STRING)
- Faculty_Name (STRING)
- Course_Credit (INT)
- Obtained_Marks_Grade (STRING)
- Out_of_Marks_Grade (STRING)
- Exam_Result (STRING)

2. Load Data into Hive Tables

The data from the CSV files is loaded into the corresponding Hive tables using the **LOAD DATA** command in the **create_and_load_tables.hql** script.

3. Data Cleaning

The `data_cleaning.hql` script performs the following cleaning operations:

- **Fill Missing Faculty Names:** Uses a self-join to fill in missing faculty names in `GradeRosterReport.csv`.
 - **Remove Unnecessary Columns:** Drops unnecessary columns like `Serial No.`, `Status`, and `Academia+LMS` from `Enrollment_Data.csv`.
 - **Update Program Name:** Extracts and updates the `Program Name` field from `Program Code/Name` in `GradeRosterReport.csv`.
 - **Handle Multiple Faculty Entries:** Extracts a single, primary entry from the `Primary Faculty` column in `Enrollment_Data.csv`.
-

4. Final Output

The cleaned data is saved in:

- `Enrollment_Data_v7.csv`
- `GradeRosterReport_v4.csv`

These are ready for further analysis and reporting.

Usage

1. Set Up Hive Environment

Ensure Apache Hive is properly installed and configured in your environment.

2. Run Table Creation and Load Script

Execute `create_and_load_tables.hql` to define schemas and load the raw data.

```
hive -f create_and_load_tables.hql
```

3. Run Data Cleaning Script

Execute `data_cleaning.hql` to perform all cleaning operations.

```
hive -f data_cleaning.hql
```

Question-2

We have created schema for the tables in Q1 along with basic cleaning, and now we want to create dimensional and fact tables for the dimensional modelling. To do so, we have to define their schemas as done in Q1 along with the fact table.

Since, it is a dimensional modelling, we have to pre-process the data and perform joins to form the fact table. Thus, some additional pre-processing will be required, specially on the subject names as all the three files have different structures of defining them altogether. Typically, fact tables are formed as a result of join on student id and course/subject name. Thus, the course/subject name needs to be pre-processed in the hiveql, so it has similar contents which essentially belong to the same course. The data is from various sources like erp, codetantra and/or LMS, thus creating different values for the same subjects.

The typical pre-processing steps that we had one are in pre-processing.hql. The details of these pre-processing along with reasoning are as follows:

1. Standardization of Text Format

- **Convert to Lowercase:**

- Using functions like LOWER() to convert all subject/course names to lowercase.
- Reason: Ensures that differences in capitalization (e.g., "Maths" vs. "maths") do not create duplicate keys.

- **Trim Whitespaces:**

- Apply the TRIM() function to remove leading and trailing spaces from text fields, especially trimming around delimiters like / and -, as evident in enrollment and grade data course fields.
- Reason: Removes accidental spaces that could lead to mismatches during joins.

- **Uniform Delimiter Replacement:**

- Use REGEXP_REPLACE() to standardize delimiters (like replacing hyphens, slashes, or multiple spaces with a single delimiter /). This is done to separate course code with course name.
- Reason: Multiple representations (e.g., "CSE-101", "CSE/101", "CSE 101") get unified to a single format.

2. Issues with attendance data:

- **Uneven course_name in attendance data:**

- Courses like "T1-24-25-AMS 211-Mathematics-3" are there in those fields, which should be ideally be "AMS 211-Mathematics-3" to maintain homogeneity with other tables.
- There are multiple rows which has email as **vishnu.raj@iiitb.org**. Those columns are essentially faculty meetings, and those rows are removed and added to error_logs table, since they are erroneous values.
- Some course names do not have any course code, and are essentially random staff/board meeting like **Audio testing Meeting by Prof Chandrashekar Ramanathan**. Those rows are removed from the table and added into error_logs table, since they are erroneous values.

- **Courses specifying batches:**

- For courses with regard to first years, in some places they have mentioned batches they are teaching like **T1-24-25-GNL 101-English(BT1-IMT1-CSE)**. So, I have removed the contents of


```
INFO : Table student_data.merged_table stats: [numFiles=1, numRows=3634, totalSize=1539904, rawDataSize=1536270, numFilesErasureCoded=0]
INFO : Completed executing command(queryId=hive_20250414181736_4d9ba148-0f5f-49dd-9ab4-fa8f4229c41f); Time taken: 1.055 seconds
3,634 rows affected (1.342 seconds)
0: jdbc:hive2://localhost:10000/>>
```

What we did was first write the python script for all the dimensional tables and pre-processed it such that on doing inner join, we will get maximum rows in the fact table. Now, the fact table has **2771 rows**, which would have been **less than 1000** without pre-processing. Then, we backtracked and form the hql queries and reported it in hql file.

The structure of fact tables is as follows:

```
CREATE TABLE IF NOT EXISTS fact_table (
    member_id STRING,
    course STRING,
    number_of_classes_attended INT,
    number_of_classes_absent INT,
    course_credit INT,
```

```

        average_attendance_percent FLOAT
    )
    ROW FORMAT SERDE 'org.apache.hadoop.hive.serde2.OpenCSVSerde'
    WITH SERDEPROPERTIES (
        "separatorChar" = ",",
        "quoteChar"      = "\""
    )
    STORED AS TEXTFILE
    TBLPROPERTIES ("skip.header.line.count" = "1");

```

The structure of all the dimension tables as defined in Q1 are as follows:-

```

CREATE TABLE IF NOT EXISTS dim_enrollment_data (
    serial_no INT,
    course_type STRING,
    student_id STRING,
    student_name STRING,
    program STRING,
    batch STRING,
    period STRING,
    enrollment_date STRING,
    primary_faculty STRING,
    subject_code_name STRING,
    section STRING
)
ROW FORMAT SERDE 'org.apache.hadoop.hive.serde2.OpenCSVSerde'
WITH SERDEPROPERTIES (
    "separatorChar" = ",",
    "quoteChar"      = "\""
)
STORED AS TEXTFILE
TBLPROPERTIES ("skip.header.line.count"="1");

CREATE TABLE IF NOT EXISTS dim_grade_roster (
    academy_location STRING,
    student_id STRING,
    student_status STRING,
    admission_id STRING,
    admission_status STRING,
    student_name STRING,
    program_name STRING,
    batch STRING,
    period STRING,
    section STRING,
    faculty_name STRING,
    course_credit INT,
    obtained_marks_grade STRING,
    out_of_marks_grade STRING,
    exam_result STRING,
    subject_code_name STRING
)

```

```

ROW FORMAT SERDE 'org.apache.hadoop.hive.serde2.OpenCSVSerde'
WITH SERDEPROPERTIES (
  "separatorChar" = ",",
  "quoteChar"     = "\""
)
STORED AS TEXTFILE
TBLPROPERTIES ("skip.header.line.count"="1");

CREATE TABLE IF NOT EXISTS dim_attendance_data (
  course STRING,
  instructor STRING,
  name STRING,
  email_id STRING,
  member_id STRING,
  number_of_classes_attended INT,
  number_of_classes_absent INT,
  average_attendance_percent FLOAT
)
ROW FORMAT SERDE 'org.apache.hadoop.hive.serde2.OpenCSVSerde'
WITH SERDEPROPERTIES (
  "separatorChar" = ",",
  "quoteChar"     = "\""
)
STORED AS TEXTFILE
TBLPROPERTIES ("skip.header.line.count"="1");

```

Firstly, we mount the csv files into the docker image folder, so as to use it for populating tables with the data.

```

keshav-chandak@keshav-chandak-HP-Pavilion-Laptop-14-ec1xxx:~/Desktop/output Q2$ docker cp attendance.csv hive4:/tmp/dim_attendance.csv
Successfully copied 2.36MB to hive4:/tmp/dim_attendance.csv
keshav-chandak@keshav-chandak-HP-Pavilion-Laptop-14-ec1xxx:~/Desktop/output Q2$ docker cp enrollment.csv hive4:/tmp/dim_enrollment.csv
Successfully copied 868kB to hive4:/tmp/dim_enrollment.csv
keshav-chandak@keshav-chandak-HP-Pavilion-Laptop-14-ec1xxx:~/Desktop/output Q2$ docker cp grade.csv hive4:/tmp/dim_grade.csv
Successfully copied 1.8MB to hive4:/tmp/dim_grade.csv
keshav-chandak@keshav-chandak-HP-Pavilion-Laptop-14-ec1xxx:~/Desktop/output Q2$ docker cp fact_table_final1.csv hive4:/tmp/fact_table.csv
keshav-chandak@keshav-chandak-HP-Pavilion-Laptop-14-ec1xxx:~/Desktop/output Q2$

```

Then, we load the csv dataset into the above schema.

The code for loading it into hql table schemas is in load_queries.hql

The corresponding hql output after loading, and select statements are as follows:

```

+-----+
+-----+
+-----+
8,495 rows selected (2.601 seconds)
+-----+
+-----+
3,101 rows selected (0.313 seconds)
+-----+
+-----+
4,477 rows selected (0.478 seconds)
+-----+

```

After this is done, we try three HiveQL analytic queries. I have utilised these three queries since it covers the utility of all the numerical columns in the dimension and fact tables.

Before starting off, since we are utilising hive as a docker image due to various issues in the installation as faced by many others, we are storing the tables everytime in our local system. So, first we load csv of dimensional tables and fact table onto the docker image: `docker cp attendance.csv`
`hive4:/tmp/dim_attendance.csv`
`docker cp enrollment.csv hive4:/tmp/dim_enrollment.csv` `docker cp grade.csv hive4:/tmp/dim_grade.csv`


```
docker cp fact_table_final.csv hive4:/tmp/fact_table.csv
```

```
keshav-chandak@keshav-chandak-HP-Pavilion-Laptop-14-ec1xxx:~/Desktop/output Q2$ docker cp attendance.csv hive4:/tmp/dim_attendance.csv
Successfully copied 2.36MB to hive4:/tmp/dim_attendance.csv
keshav-chandak@keshav-chandak-HP-Pavilion-Laptop-14-ec1xxx:~/Desktop/output Q2$ docker cp enrollment.csv hive4:/tmp/dim_enrollment.csv
Successfully copied 868kB to hive4:/tmp/dim_enrollment.csv
keshav-chandak@keshav-chandak-HP-Pavilion-Laptop-14-ec1xxx:~/Desktop/output Q2$ docker cp grade.csv hive4:/tmp/dim_grade.csv
Successfully copied 1.8MB to hive4:/tmp/dim_grade.csv
keshav-chandak@keshav-chandak-HP-Pavilion-Laptop-14-ec1xxx:~/Desktop/output Q2$ docker cp fact_table_final1.csv hive4:/tmp/fact_table.csv
keshav-chandak@keshav-chandak-HP-Pavilion-Laptop-14-ec1xxx:~/Desktop/output Q2$
```

Query-1

Objective:

To compute the CGPA (Cumulative Grade Point Average) for each student based on the grade obtained and course credits.

Approach:

- Join **dim_grade_roster** and **fact_table** on **student_id** and **subject_code_name**.
- Use a weighted sum of grade points (based on institutional grading system) multiplied by **course_credit**.
- Divide total weighted grade points by total credits to derive CGPA.
- Order results by CGPA and then by total credits in descending order.

Query

```
SELECT
  g.student_id,
  SUM(g.course_credit) AS total_credits_completed,
  SUM(CASE
    WHEN g.obtained_marks_grade = 'A' THEN 4.0 * g.course_credit
    WHEN g.obtained_marks_grade = 'A-' THEN 3.7 * g.course_credit
    WHEN g.obtained_marks_grade = 'B+' THEN 3.4 * g.course_credit
    WHEN g.obtained_marks_grade = 'B' THEN 3.0 * g.course_credit
    WHEN g.obtained_marks_grade = 'B-' THEN 2.7 * g.course_credit
    WHEN g.obtained_marks_grade = 'C+' THEN 2.4 * g.course_credit
    WHEN g.obtained_marks_grade = 'C' THEN 2.0 * g.course_credit
    WHEN g.obtained_marks_grade = 'D' THEN 1.7 * g.course_credit
    ELSE 0.0
  END) / SUM(g.course_credit) AS cgpa
FROM dim_grade_roster g
JOIN fact_table f
  ON g.student_id = f.member_id
  AND g.subject_code_name = f.course
GROUP BY g.student_id
ORDER BY cgpa DESC, total_credits_completed DESC;
```

Use Case:

This query is essential for academic performance analysis, ranking students, and eligibility for honors or scholarships.

```
-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
VERTICES      MODE      STATUS  TOTAL  COMPLETED  RUNNING  PENDING  FAILED  KILLED
-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
Map 3 ..... container    SUCCEEDED    1         1         0         0         0         0
Map 1 ..... container    SUCCEEDED    1         1         0         0         0         0
Reducer 2 ..... container SUCCEEDED    1         1         0         0         0         0
-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
VERTICES: 03/03 [=====>>>] 100% ELAPSED TIME: 2.34 s
-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
INFO : Completed executing command(queryId=hive_20250414133532_77c2051d-3fbd-4fb1-92b1-c8a381e49198); Time taken: 5.485 seconds
-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
|          g.student_id          | total_credits_completed |          cgpa          |
-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
| 006ebffbd115df9b6ef0e30a5cf33a86d6544a0bdb4b2e0c5f01addf199fbe8f | 28.0 | 1.95 |
| 01021eb63ad8ca36d35a6fd4ead1a931e4dc4b74999a5cf98c7900d8540c97ae | 8.0 | 1.475 |
| 01104f71b9089725f8209bb949fb92555b90730dd4213561908386f1f0269a2b | 22.0 | 3.0090909090909084 |
| 0133dbf630dcec089bb08ca3c4ec094ef4d383b985452330649c99a8acd5001a | 28.0 | 2.2857142857142856 |
| 01e748f6f48344ff2bf1f20e5eb76b7411c8751af41798ff01d97fddae5d4234 | 12.0 | 3.233333333333333 |
| 03c401666f88bd87df6663255493524ba394e8db25ba9af794c9f6bc0c03f12b | 26.0 | 3.423076923076923 |
| 03e8af13a98d6f1287619ac0890c632fa203419b6f65a005c6c9d2f8478fe282 | 26.0 | 2.8999999999999995 |
| 03f205b589909f0ea18950c4fac7e7d125a61a992e33556e8a3a8b0615ab0ab4 | 32.0 | 2.21875 |
| 047236cfacc85ccce880c7b1b257e321af0ef1dd290899de7d6f9319decda76 | 32.0 | 2.4 |
| 075e7f21e42b4a5fb6e97df2bd17e65a0af0e5b11f547bfecce4ca690a2ece98e | 32.0 | 3.1125 |
| 075f4288380a972f084731c23f3ae382165107e4c5a2a2cd853633a96046fed | 24.0 | 2.1666666666666667 |
| 076449087afdae0e4172c37b1c10b693248751418392ad649ef57a52ad6e0e14 | 26.0 | 2.2923076923076926 |
| 0821a962c2726e5df442dc86f74a371ce338c2436dd2e566f85f07883c5271c2 | 28.0 | 3.5357142857142856 |
| 086ffcf64ba1b317ff114d2d3dc632675ae75ee82788a8fa0b31e6be050394d | 28.0 | 3.7642857142857147 |
| 08aa713e1d2c465191d99525020cf07f773e107a506a44229ef7f500ef498dd | 26.0 | 1.4615384615384615 |
-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
| f7b37b09dd10930d9a0132e26d2830ca8677ad11d0f666db6fa0724fe57a1fff | 22.0 | 2.0636363636363635 |
| f800cfdc8d739f2d384761d93f76d5f8d4d5c24f8b63f96556a754e6c1f86c8c | 24.0 | 2.4166666666666665 |
| f853b03aaf270f8f8b6cab1ac5003975ffc2e14ce0f8d696e0f90d5c7e80421b | 32.0 | 3.09375 |
| f9746d5926e1ef8be988f4a01b8897189476a4792deee63c7aa37e2d31b862a3 | 22.0 | 2.9272727272727277 |
| f9a66b0fe2de779b86a5f40937feb83c080449e91f30eb7454b32d2d7295b6 | 22.0 | 1.7363636363636366 |
| f9c3e40f66a95bfff6864d2daff1a29d32b55d0034e5753ae9095585f0202314e | 36.0 | 2.1055555555555556 |
| fa30950bc068d2bff9c983cb0853be94e0f15ba6fca5468c567db2ca275a7275 | 32.0 | 2.09375 |
| fa97ea0f7b79d3347a03f5cdc5e96188d59f7e7098a0cec26b28d2f804fcf205 | 32.0 | 2.03125 |
| fb82641a70b62444754aaca4126cf6d6566970fe04c5746b7f97312613a2f7fa | 32.0 | 3.375 |
| fbd0443bf1e0d231601b6aff94a29877222aca65946506425863c35151df2084 | 22.0 | 1.8636363636363635 |
| fc1e3958bf58979da2cd0fd53a5a62ba037f7eb11aeb44e08b2ea5f37cc2fffb | 36.0 | 2.1388888888888889 |
| fc43072bf0449e0f4f3743a9fb44d63507c0444bf6db744044311fb0f406bce | 28.0 | 3.1999999999999997 |
| fc4535a76a801757ff741a0cf4f9aef52866e36e06aacc43239945bd0cca113c | 28.0 | 2.9499999999999997 |
| fc5f93239ec1b27fd8bf7174a1f68e953d57e0b86e3c910135d02658a01a26ed | 26.0 | 1.9 |
| fcfa55660b5d441de2ef2e9b0b95b18c33a3f4853acdd231fea1eddd58dec1ee | 22.0 | 1.6363636363636365 |
| fcfbf656fb89ac195f2d0a8393c61f314a8449184a2f72349eef90b477c6c37b | 12.0 | 1.9833333333333334 |
| fd9709ae2b08802a0cfc32aa1971dd29c0de7c8b4be3cc07a1cb968fe2405ed5 | 28.0 | 1.3642857142857143 |
| fdb1bf0b3ff8d8048103388f108794de4164bbe8dbdf7d898a6036965cc2f292 | 28.0 | 2.9285714285714284 |
| fe6cacdcbbf5892a3583e6ec13530f2e6ea7c6c75a90fcced9a2645e7200033 | 28.0 | 2.8928571428571423 |
| fedafcd150b9a17932760554a0ec9208266957a49da49214f4f9c7e1776f340d | 22.0 | 2.8636363636363633 |
| fff6358e8fa8dce631d81990d463738796e3eb5cb545a29edad662cd92864cbfb | 8.0 | 0.25 |
| ffba274d8a68b64e86980a5d807a0057faa389d2c7a5857424d47dc960e8c434 | 12.0 | 2.4166666666666665 |
| ffd48b5414c5c285193c34544de015ed643829e5bf39c79b107a5c41aaa612dd | 28.0 | 2.857142857142857 |
| ffe3d002fbf6b6c402030b73c54bacef8c8e9c4b5d7108ac2c8f9b206f0f177 | 26.0 | 2.4461538461538463 |
-----+-----+-----+-----+-----+-----+-----+-----+-----+-----+
524 rows selected (6.54 seconds)
```

Time Elapsed: 6.54 seconds

Query-2

Objective:

To determine the number of students taught, average attendance, and maximum course credit for each faculty.

Approach:

- Join `dim_grade_roster` and `fact_table` on student and course.
- Filter for only those students who have passed (`exam_result = 'Pass'`).
- Aggregate data to:
 - Count distinct students per faculty.
 - Calculate average attendance using `average_attendance_percent`.
 - Determine the highest credit course taught by each faculty.

Use Case:

This helps analyze faculty engagement, workload distribution, and effectiveness in teaching based on student attendance and course difficulty.

Query:

```
SELECT
  g.faculty_name,
  COUNT(DISTINCT g.student_id) AS num_students,
  AVG(f.average_attendance_percent) AS avg_attendance,
  MAX(g.course_credit) AS max_course_credit
FROM fact_table f
JOIN dim_grade_roster g
  ON f.member_id = g.student_id
  AND f.course = g.subject_code_name
WHERE g.exam_result = 'Pass'
GROUP BY g.faculty_name;
```

g.faculty_name	num_students	avg_attendance	max_course_credit
Amit Chattopadhyay	159	84.39371069182388	4.0
Ashish Choudhury	6	80.73333333333333	4.0
Badrinath Ramamurthy	120	87.2225	2.0
G. Srinivasa Raghavan	4	88.675	4.0
Jaya Sreevalsan Nair	1	70.8	4.0
Jyotsna Bapat	2	97.2	4.0
Karthikeyan Vaidyanathan	1	85.7	4.0
Kurian Polachan	91	86.91978021978026	4.0
Manisha Kulkarni	119	76.56722689075629	4.0
Meenakshi D. Souza	3	86.26666666666667	4.0
Nanditha Rao	42	66.87857142857142	4.0
Pillalamarri Sridhar	160	80.71	4.0
Preeti Mudliar	33	80.2	4.0
Priyanka Das	6	77.18333333333335	4.0
Priyanka Sharma	280	66.44857142857144	2.0
Prof. Amrita Mishra	120	79.95333333333339	4.0
S. Malapaka	166	80.00903614457827	4.0
Sachit Rao	150	74.71743119266057	4.0
Sakshi Arora	30	73.76666666666667	4.0
Srinath Srinivasa	3	88.90000000000002	4.0
Srinivas Vivek	198	77.55353535353527	4.0
Sujit Kumar Chakrabarti	160	86.43624999999997	2.0
Sushree Behera	4	81.825	4.0
Thangaraju B.	149	92.32364864864864	4.0
Tulika Saha	120	73.93666666666667	2.0
Uttan Kumar	2	28.0	4.0
V. Sridhar	313	83.2861271676299	4.0
Vinod Reddy	5	67.03999999999999	4.0
Vinu E. V.	59	87.05762711864405	4.0
Viswanath G.	145	85.38620689655166	4.0

30 rows selected (0.932 seconds)

Time Elapsed:0.912 seconds

Query-3

Objective:

To identify students who have an attendance percentage below 75% in any course.

Approach:

- Join `dim_grade_roster` and `fact_table` on `student_id` and `subject_code_name`.
- Calculate overall attendance percentage as $(\text{classes_attended} / (\text{attended} + \text{absent})) * 100$:
- Filter (`HAVING`) to return only those records with less than 75% attendance.

Query:

Use Case:

14144	fcfbf656fb89ac105f2d0a8393c61f314a849184a2f72349eef90b477c6c37b VLS 864/Embedded Systems Design 16.0 8.0 66.6666666666
66667	fd9709ae2b08802a0fc32aa1971dd29c0de7c8b4be3cc07a1cb968fe2405ed5 EGC 112/Programming 1B (Python Programming) 7.0 4.0 63.636363636
36363	fdb1bf0b3ff8d8048103388f108794de164bbe8bdbf7d898a6036965cc2f292 AMS 101/Probability & Statistics 68.0 32.0 68.0
	fdb1bf0b3ff8d8048103388f108794de164bbe8bdbf7d898a6036965cc2f292 AMS 103/Calculus 92.0 40.0 69.696969696
9697	fdb1bf0b3ff8d8048103388f108794de164bbe8bdbf7d898a6036965cc2f292 EGC 102/Digital Design 25.0 9.0 73.529411764
70588	fdb1bf0b3ff8d8048103388f108794de164bbe8bdbf7d898a6036965cc2f292 EGC 112/Programming 1B (Python Programming) 7.0 4.0 63.636363636
36363	fdb1bf0b3ff8d8048103388f108794de164bbe8bdbf7d898a6036965cc2f292 GNL 101/English 7.0 4.0 63.636363636
36363	fe6cacdcbbf5892a3583e6ec13530f2e6ea7c6c75a90fcccd9a2645e7200033 AMS 101/Probability & Statistics 4.0 28.0 58.823529411
7647	fe6cacdcbbf5892a3583e6ec13530f2e6ea7c6c75a90fcccd9a2645e7200033 AMS 103/Calculus 48.0 56.0 46.153846153
84615	fe6cacdcbbf5892a3583e6ec13530f2e6ea7c6c75a90fcccd9a2645e7200033 EGC 102/Digital Design 17.0 10.0 62.962962962
96296	fe6cacdcbbf5892a3583e6ec13530f2e6ea7c6c75a90fcccd9a2645e7200033 GNL 101/English 0.0 1.0 0.0
	fe6cacdcbbf5892a3583e6ec13530f2e6ea7c6c75a90fcccd9a2645e7200033 HSS 111/Economics-1 2.0 10.0 16.666666666
666668	fedafcd150b9a17932760554a0ec9208266957a49da49214f4f9c7e1776f340d GNL 101/English 7.0 3.0 70.0
	ff6358e8fa8dce631d81990d463738796c3eb5cb545a29edad62cd92864cbfb VLS 505/System design with FPGA 6.0 3.0 66.666666666
66667	ffba274d8a68b64e86980a5d807a0057faa389d2c7a5857424d47cd960e8c434 AIM 511/Machine Learning 0.0 4.0 0.0
	ffe3d002fbf6b6c4020303b73c54bcf8c8e9c4b5db7108ac2c8f9b206f0f177 EGC 111/Programming 1A (C Programming) 32.0 28.0 53.333333333
333336	ffe3d002fbf6b6c4020303b73c54bcf8c8e9c4b5db7108ac2c8f9b206f0f177 GNL 101/English 7.0 3.0 70.0
+-----+	
850 rows selected (1.23 seconds)	

Note: You might be seeing that I am using only two tables in the queries, but since the fact table contains all the numerical data regarding attendance, thus **dim_attendance** table is not used. Similarly enrollment data had no numerical values, thus it is not part of join, as there cannot be any analytical query possible.

The error_log.csv in the output folder of Q2 contains the inconsistent and erroneous data that we found out earlier. Since, the rest of the data was pre-processed and retained in the table, only erroneous values in the attendance table has been copied to the error_logs table.

INFO : Executing command(queryid:hive_20250414283613_49080216-2d0d-4ec4-a66a-8a95845ecd08) : select * from error_log limit 20									
INFO : Completed executing command(queryid:hive_20250414283613_49080216-2d0d-4ec4-a66a-8a95845ecd08) : Time taken: 0.0 seconds									
error_log_course									
error_log_member_id	error_log_number_of_classes_attended	error_log_instructor	error_log_name	error_log_email_id					
Audio testing Meeting by Prof. Chandrashekar Ramanathan : [Meeting] rcgllttb.ac.in									
001b9294c82b556d472ac8b71154b15bb446af7	397360232920f921218d0dc543ae7c309e46640d934a0314de999f5112	0	dffb2ca811bbeeb59e0386294d92bac662c65431ae68c05214cc25681dccc	67597f69e9cb5c6d44cc4d	0	0.00%			
Demo Meeting by Vishnu Raj : [Meeting] vishnu.raj@gllttb.org									
42c6c17154b15bb446af7	39736022e9320f921218d0dc543ae7c309e46640d934a0314de999f5112	0	dffb2ca811bbeeb59e0386294d92bac662c65431ae68c05214cc25681dccc	67597f69e9cb5c6d44cc4d001b9294c82b56d	0	0.00%			
Meeting by Vishnu Raj : [Meeting] vishnu.raj@gllttb.org									
42f2ac8c17154b15bb446af7	397360232920f921218d0dc543ae7c309e46640d934a0314de999f5112	0	dffb2ca811bbeeb59e0386294d92bac662c65431ae68c05214cc25681dccc	67597f69e9cb5c6d44cc4d001b9294c82b56d	0	0.00%			
Meeting by Vishnu Raj : [Meeting] vishnu.raj@gllttb.org									
42f2ac8c17154b15bb446af7	39736022e9320f921218d0dc543ae7c309e46640d934a0314de999f5112	0	dffb2ca811bbeeb59e0386294d92bac662c65431ae68c05214cc25681dccc	67597f69e9cb5c6d44cc4d001b9294c82b56d	0	0.00%			
Audio testing Meeting by Prof. Chandrashekar Ramanathan : [Meeting] rcgllttb.ac.in									
b80a67506e940d327473680806a87cd	4896299d574c8a31c3c05c88f7b752b106282c58f68d27a52cbaf98de6	1	0d094ce9e94c0f6f1807c616c3211eaa1ae726295f98b53a5627de145	f29a2b7844b7ab13f3bad04aef67bd18	0	100.00%			
Information Economics and Product Finance vsrldhargllttb.ac.in, amtpkraskh@gllttb.ac.in									
4e3660c281534c9ccdde	74e748f6f381a4f2bf2f20e1274d91798f49277fdde54234	12	b562ceb75215650ed95b2177426f08b2098d5a47c047a57531019776aa791	e2ff6f13a15ce9c717b4fa8f1f84db4392caec5	0	66.70%			
Extra class by Prof. Chandrashekar Ramanathan : [Meeting] rcgllttb.ac.in									
b362490d15c13865d443750babdd9e5	680a11b23d9282dd02f49381bbde08f5344d15836321548418c0aac4d71b3	1	0d092dc2fa5bfbd764eb6d02315a237295aa6cab4265bc62117b915248	1a3da6d52318cd457d5410d61c547282	0	100.00%			
Extra class by Prof. Chandrashekar Ramanathan : [Meeting] rcgllttb.ac.in									
707339dbccf85e79fd7090730c31e0a3	fa0a4237743bc276ae2a86e9078c2327d3fa15875ad4bfcfd92b650be74c	0	7044053013692511bcf7c91f78e5a1fe0858298266824beff80786fa76b2	b15c945832651d2b2ae775d60dafae8	0	100.00%			
Extra class by Prof. Chandrashekar Ramanathan : [Meeting] rcgllttb.ac.in									
a056ec0117f725738493ee4908ee0	76e110880986885dad3791c2b2c339df6219840c0e44ccc60f5396ea0fd	1	b0132c96ebad7fc18734c746b8bd7d625955b67ab0b7776ad9bf9d1d61cae	96e6d007f83322774de8e96c0990e220	0	100.00%			
Extra class by Prof. Chandrashekar Ramanathan : [Meeting] rcgllttb.ac.in									
809c8b73d9b2276e6a31e811b0dddf	7d430528aea0aabb6ed26a0c37ee7d574cbb8c429f6f7f17a0c4df9650cf	1	fec8509bfa15b8788385fe3f52d14076a77c44db31fe71085a9f92ce60	397b0649440902333a5fd726bb3538ea	0	100.00%			
Audio testing Meeting by Prof. Chandrashekar Ramanathan : [Meeting] rcgllttb.ac.in									
c4f5e72043502ce242aef98c5228303aaacbb1	af9d081b2154959d945d40beac2d1c5a2ae2d894cc08dca0c019277aa10	0	8c806a47dae5d3ad83ab82bd09a42161e5eb1eabaf72e47bed755db876f4662	667670d3f9edcb36d9cac33	0	0.00%			
Demo Meeting by Vishnu Raj : [Meeting] vishnu.raj@gllttb.org									
424a6f98c5228303aaacbb1	af9d080b152194599d945d40beac2d1c5a2ae2d894cc08dca0c019277aa10	0	c806a47dae5d3ad83ab82bd09a42161e5eb1eabaf72e47bed755db876f4662	667670d3f9edcb36d9cac33c4f5e72043502ce2	0	0.00%			
Extra class by Prof. Chandrashekar Ramanathan : [Meeting] rcgllttb.ac.in									
424a6f98c5228303aaacbb1	af9d081b2194599d945d40beac2d1c5a2ae2d894cc08dca0c019277aa10	0	c806a47dae5d3ad83ab82bd09a42161e5eb1eabaf72e47bed755db876f4662	667670d3f9edcb36d9cac33c4f5e72043502ce2	0	0.00%			
Meeting by Vishnu Raj : [Meeting] vishnu.raj@gllttb.org									
424a6f98c5228303aaacbb1	af9d080b152194599d945d40beac2d1c5a2ae2d894cc08dca0c019277aa10	0	c806a47dae5d3ad83ab82bd09a42161e5eb1eabaf72e47bed755db876f4662	667670d3f9edcb36d9cac33c4f5e72043502ce2	0	0.00%			
Extra class by Prof. Chandrashekar Ramanathan : [Meeting] rcgllttb.ac.in									
8a390deb5eef8ae5a391678197176af	81891f337398f6d6e9436a75fcd78759386e842ab430cddffce933b2212	1	7358abc91cad1a6e038982e28f1d2139718e2dc2010857c9b06c083b14216fa	1141b0a1b90638887aacbdf94eb6c4a	0	100.			

Question-3

Now on running the hiveql, we set Hive properties for dynamic bucketing:

1. SET hive.enforce.bucketing=true;
2. SET hive.enforce.sorting=true;

```
0: jdbc:hive2://localhost:10000/> SET hive.enforce.bucketing=true;
No rows affected (0.018 seconds)
0: jdbc:hive2://localhost:10000/> SET hive.enforce.sorting=true;
No rows affected (0.009 seconds)
0: jdbc:hive2://localhost:10000/> █
```

Now, the schema for the optimised dimensional and fact tables using data modelling concepts, and the effective concept of how the partitioning and bucketing will increase query performance. The schema for the tables are as follows:-

```
CREATE TABLE IF NOT EXISTS dim_grade_roster_optimised (
    academy_location STRING,
    student_id STRING,
    student_status STRING,
    admission_id STRING,
    admission_status STRING,
    program_name STRING,
    batch STRING,
    period STRING,
    faculty_name STRING,
    course_credit INT,
    obtained_marks_grade STRING,
    out_of_marks_grade STRING,
    exam_result STRING,
    subject_code_name STRING
)
PARTITIONED BY (section STRING)
CLUSTERED BY (student_id) INTO 8 BUCKETS
STORED AS ORC;

CREATE TABLE IF NOT EXISTS dim_attendance_data_optimised (
    instructor STRING,
    name STRING,
    member_id STRING,
    number_of_classes_attended INT,
    number_of_classes_absent INT,
    average_attendance_percent FLOAT
)
PARTITIONED BY (course STRING)
CLUSTERED BY (member_id) INTO 8 BUCKETS
STORED AS ORC;
```



```
CREATE TABLE IF NOT EXISTS fact_table_optimised (  
    member_id STRING,  
    course STRING,  
    number_of_classes_attended INT,  
    number_of_classes_absent INT,  
    course_credit INT,  
    average_attendance_percent FLOAT  
)  
CLUSTERED BY (member_id) INTO 8 BUCKETS  
STORED AS ORC;  
  
CREATE TABLE IF NOT EXISTS dim_enrollment_data_optimised (  
    serial_no INT,  
    course_type STRING,  
    student_id STRING,  
    program STRING,  
    batch STRING,  
    period STRING,  
    enrollment_date STRING,  
    primary_faculty STRING,  
    section STRING  
)  
PARTITIONED BY (subject_code_name STRING)  
CLUSTERED BY (student_id) INTO 8 BUCKETS  
STORED AS ORC;
```

You can see that, we have partitioned and bucketed it into optimised tables.

The justification for that is as follows:-

1. **dim_grade_roster_optimised**

- **Partitioned by section:**

- Improves query performance for section-specific queries.
- Ideal for filtering when analyzing grades per class or section.

- **Clustered by student_id:**

- Boosts performance for student-wise joins (e.g., with attendance or fact table).
- Enables efficient aggregation operations like CGPA computation.

2. **dim_attendance_data_optimised**

- **Partitioned by course:**

- Optimizes queries analyzing attendance by course.
- Reduces scan overhead for course-level reports.

- **Clustered by member_id:**

- Enhances performance for per-student attendance analysis.
- Useful in joins and aggregations involving individual students.

3. **fact_table_optimised**

- **No Partitioning:**
 - Acts as a central fact table joined with all dimensions.
 - Uniform query access across multiple attributes, so partitioning might not help.
- **Clustered by member_id:**
 - Speeds up joins with **dim_grade_roster_optimised** and **dim_attendance_data_optimised**.
 - Supports student-wise performance analysis (e.g., attendance + credit aggregation).

4. **dim_enrollment_data_optimised**

- **Partitioned by subject_code_name:**
 - Reduces data scanned for subject-specific queries or filters.
 - Common in analytics related to specific courses.
- **Clustered by student_id:**
 - Improves query performance for student-based tracking.
 - Useful for joins with grade and fact tables on **student_id**.

Query-1

Objective:

To compute the CGPA (Cumulative Grade Point Average) for each student based on the grade obtained and course credits.

Approach:

- Join **dim_grade_roster_optimised** and **fact_table_optimised** on **student_id** and **subject_code_name**.
- Use a weighted sum of grade points (based on institutional grading system) multiplied by **course_credit**.
- Divide total weighted grade points by total credits to derive CGPA.
- Order results by CGPA and then by total credits in descending order.
- Since, we have done effective clustering and partitioning, we get the results in much lesser time, greater query performance.

Use Case:

This query is essential for academic performance analysis, ranking students, and eligibility for honors or scholarships.


```

2acad14ae711bdd8249e4f49c85fe872cb75313e0dc39c20c760d420a0072243 | 22.0 | 2.3909090909090907 |
6451f1fdbfb51e85c217fc58523ac177fe9c1e59b00d11cf65d47035fdb720b1 | 28.0 | 2.3785714285714286 |
b0026ddcd2635476e72f335b7ded6341ede34eb5f8f3e2ed34aa60062d3934fd | 32.0 | 2.375 |
01021eb63ad8ca36d35a6fd4ead1a931e4dc4b74999a5cf98c7900d8540c97ae | 8.0 | 2.35 |
5db0ea3e96305d5b2434e0a9e3657a76c67509c8327c7e47fd54d1b4b9063f31 | 26.0 | 2.3307692307692305 |
4caf9268ea5658127bf8512445be6922eac2357c8c52b5c5a2c631cae6af0c5d | 22.0 | 2.290909090909091 |
86b2b4629113bb3a78373aa25f95a8dccc65676327b2c3e36109872ac9bacc2c | 12.0 | 2.266666666666667 |
447f6ae3c7fd293dabbad856074c77f5ac90b133b9b114cc8080e78770d60882 | 22.0 | 2.2545454545454544 |
ad841dec8c5b2f1952dc51dd60adff513a672c4ddea7228935127ce06c875c20a | 22.0 | 2.2363636363636363 |
c4ff6797d1fb4433553653d82b0289c32a3c7837c7012da48ecab2ac9c01ee3a | 32.0 | 2.1875 |
8777036516faed4eabf100af059a4c3e157ceaaebcdfa28191d593415f64204 | 28.0 | 2.157142857142857 |
46afc932a74d834d21d0547dee5b8bffe616f40a9b3b77dd47c045c2101cc9 | 32.0 | 2.1 |
cae5018bebe2ccff689e80a84c44d7d3a6acac9949e72e364e03c5e6116b9bed | 32.0 | 2.1 |
19c5c74b92596d69c552ea81c9aab4370c91a8753e1b64020a7cf16367ea3ea1 | 26.0 | 2.0615384615384613 |
+-----+-----+-----+
| g.student_id | total_credits_completed | cgpa |
+-----+-----+-----+
b7f97c4154f2b34129c7f5192e1c40e1436ec1f742924fddb0c19252dc5a15bb | 32.0 | 2.025 |
9886071454e243de3f7fcd672bc754d453b29a5f08e6c6e0df0c5cf8b47f4362 | 4.0 | 2.0 |
1d26c5cdc02e2b8d9ea7983ca28fa91d58e2755852f9ff5d2321a18e21d3b49 | 4.0 | 2.0 |
1b5b60677927228f94b20a68dadf069e43e87a6ebeeabb81cff935eeab4f67 | 28.0 | 1.807142857142857 |
8177fca161b90d83cee14b5e9162f828670d8035a199b48bb5110432b623e9a7 | 22.0 | 1.736363636363636 |
d24d0df17e3bba38e89f2eda4c03d9b30c756f4fa6aeba9ff7f3f8cb7e78bca | 26.0 | 1.6846153846153844 |
08aa713e1d2c465191d99525020cf07f773e107a506a44229e7fffb500efd98dd | 26.0 | 1.6230769230769229 |
2b6a85597239bfe683c37419733fb3a9db6d8c4abff93fa6db9db6f3bca9d493 | 28.0 | 1.5999999999999999 |
99f22d27d8c07ad9de06b443582e2346c5fcd9b3b55ab03e562a5c0c4c158a | 28.0 | 1.4928571428571427 |
fd9f09ae2b08802a0cfc32aa1971dd29c0de7c8b4be3cc07a1cb968fe2405ed5 | 28.0 | 1.4785714285714284 |
882faaed944cce28b59a882b46075b76dad00b0580d3012800a19a25ae9b3221 | 28.0 | 1.4000000000000001 |
3a2e34b3ebca5885323eb7b26d74eab2436cab04d22897c099635d550c9e9201 | 22.0 | 1.309090909090909 |
df8239ca5372ac918ccc321ea281f93ca096766e88f3783471b81c7edc720b63 | 28.0 | 1.307142857142857 |
41a9fffb21135b6c0a3007931bdfe1ec944ab4434f1435924a008aa9e3a3ec15f | 26.0 | 1.2769230769230768 |
9bb1f24866e6e0ab55847f85f87829cd4f7be72d1d341c9e514f14602e4e30d4 | 28.0 | 1.2642857142857142 |
075f4288380a972f084731c23f3ae382165107e4c5a2a2cd85363d3a96046fed | 24.0 | 1.1333333333333333 |
e03396384ee196698bfc8bc0e21b2af1f2d72950c2d505a6be57261f1a2b6634 | 28.0 | 1.0357142857142858 |
84c39af59e43f9068fb7d4de358f0bbf67c90947463da8fe264c40c6895502e6 | 22.0 | 0.890909090909091 |
5e66c5f5200f0426105d3639378ede436e1b0611b183df366fd42b5b4b3e7bac | 28.0 | 0.7585714285714285 |
9582fbc05cf3288085a5d745452cebc2255674776c23c0495cddb6e852418a02 | 28.0 | 0.5285714285714286 |
7fd5a24c7f7cae6655cc5747682409abc28f5872ff4d868bb033310ab07b1fa0c | 24.0 | 0.0 |
14c1e6fdb35fc08be0fe6b496924fdb2280c15bb2ab972979e4ca9d4c8d73a4e2 | 20.0 | 0.0 |
56a2e07bec0c4250925b2bb8579ac06a309404e9d03d911627b986a2f8ad57a7 | 8.0 | 0.0 |
746fbb665bfd41bf0470020cf596bea17d648b383f88f991408c55c191059b59 | 8.0 | 0.0 |
+-----+-----+-----+
524 rows selected (1.043 seconds)
0: jdbc:hive2://localhost:10000/

```

Time Elapsed:1.643 seconds

Query-2

Objective:

To determine the number of students taught, average attendance, and maximum course credit for each faculty.

Approach:

- Join **dim_grade_roster_optimised** and **fact_table_optimised** on student and course.
- Filter for only those students who have passed (**exam_result = 'Pass'**).
- Aggregate data to:
 - Count distinct students per faculty.
 - Calculate average attendance using **average_attendance_percent**.
 - Determine the highest credit course taught by each faculty.
- Since, we have done effective clustering and partitioning, we get the results in much lesser time, greater query performance.

Use Case:

This helps analyze faculty engagement, workload distribution, and effectiveness in teaching based on student attendance and course difficulty.

	Nanditha Rao		42		66.87857142857142		4.0		
	Pillalamarri Sridhar		160		80.71		4.0		
	Preeti Mudliar		33		80.2		4.0		
	Priyanka Das		6		77.18333333333335		4.0		
	Priyanka Sharma		280		66.44857142857144		2.0		
	Prof. Amrita Mishra		120		79.95333333333339		4.0		
	S Malapaka		166		80.00903614457827		4.0		
	Sachit Rao		150		74.71743119266057		4.0		
	Sakshi Arora		30		73.76666666666667		4.0		
	Srinath Srinivasa		3		88.90000000000002		4.0		
	Srinivas Vivek		198		77.55353535353527		4.0		
	Sujit Kumar Chakrabarti		160		86.43624999999997		2.0		
	Sushree Behera		4		81.825		4.0		
	Thangaraju B		149		92.32364864864864		4.0		
	Tulika Saha		120		73.93666666666667		2.0		
	Uttam Kumar		2		28.0		4.0		
	V Sridhar		313		83.2861271676299		4.0		
	Vinod Reddy		5		67.03999999999999		4.0		
	Vinu E V		59		87.05762711864405		4.0		
	Viswanath G		145		85.38620689655166		4.0		
-----+									
30	rows selected (0.793 seconds)								

Time Elapsed:0.793 seconds

Query-3

Objective:

To identify students who have an attendance percentage below 75% in any course.

Approach:

- Join **dim_grade_roster_optimised** and **fact_table_optimised** on **student_id** and **subject_code_name**.
- Calculate overall attendance percentage as $(classes_attended / (attended + absent)) * 100$:
- Filter (**HAVING**) to return only those records with less than 75% attendance.
- Since, we have done effective clustering and partitioning, we get the results in much lesser time, greater query performance.

Use Case:

Used for academic warnings, eligibility checks for exams, and enforcing minimum attendance policies.

	fd9709ae2b08802a0cfc32aa1971dd29c0de7c8b4be3cc07a1cb968fe2405ed5		EGC 112/Programming 1B (Python Programming)		7.0		4.0		63.63636363636363
	fdb1bf0b3ff8d8048103388f108794de4164bbe8bdf7d898a6036965cc2f292		AMS 101/Probability & Statistics		68.0		32.0		68.0
	fdb1bf0b3ff8d8048103388f108794de4164bbe8bdf7d898a6036965cc2f292		AMS 103/Calculus		92.0		40.0		69.69696969696969
	fdb1bf0b3ff8d8048103388f108794de4164bbe8bdf7d898a6036965cc2f292		EGC 102/Digital Design		25.0		9.0		73.52941176470588
	fdb1bf0b3ff8d8048103388f108794de4164bbe8bdf7d898a6036965cc2f292		EGC 112/Programming 1B (Python Programming)		7.0		4.0		63.63636363636363
	fdb1bf0b3ff8d8048103388f108794de4164bbe8bdf7d898a6036965cc2f292		GNL 101/English		7.0		4.0		63.63636363636363
	fe6cacdccebbf5892a3583e6ec13530f2e6ea7c6c75a90fcccd9a2645e7200033		AMS 101/Probability & Statistics		40.0		28.0		58.8235294117647
	fe6cacdccebbf5892a3583e6ec13530f2e6ea7c6c75a90fcccd9a2645e7200033		AMS 103/Calculus		48.0		56.0		46.15384615384615
	fe6cacdccebbf5892a3583e6ec13530f2e6ea7c6c75a90fcccd9a2645e7200033		EGC 102/Digital Design		17.0		10.0		62.96296296296296
	fe6cacdccebbf5892a3583e6ec13530f2e6ea7c6c75a90fcccd9a2645e7200033		GNL 101/English		0.0		1.0		0.0
	fe6cacdccebbf5892a3583e6ec13530f2e6ea7c6c75a90fcccd9a2645e7200033		HSS 111/Economics-1		2.0		10.0		16.666666666666668
	fedafcd150b9a17932760554a0ec9208266957a49da49214f4f9c7e1776f340d		GNL 101/English		7.0		3.0		70.0
	ff6358e8fa8dce631d81990d463738796e3eb5cb545a29edad662cd92864cbfb		VLS 505/System design with FPGA		6.0		3.0		66.66666666666667
	ffba274d8a68b64e86980a5d807a0057faa389d2c7a5857424d47dc960e8c434		AIM 511/Machine Learning		0.0		4.0		0.0
	ffe3d002fbf6b6c4020303b73c54bcef8c8e9c4b5db7108acc2c8f9b206f0f177		EGC 111/Programming 1A (C Programming)		32.0		28.0		53.33333333333333
	ffe3d002fbf6b6c4020303b73c54bcef8c8e9c4b5db7108acc2c8f9b206f0f177		GNL 101/English		7.0		3.0		70.0
-----+									
850	rows selected (1.018 seconds)								

Time Elapsed:1.018 seconds

Comparsion With and Without Bucketing

: Comparison of HiveQL Query Execution Time With and Without Bucketing and Partitioning

Query	Without (seconds)	With (seconds)
Query 1	6.54	1.643
Query 2	0.912	0.793
Query 3	1.23	1.018

Here, we can clearly see an increase in the query performance where the elapsed time has decreased by almost 4 times in some cases. But, the create and loading data into the optimised tables takes ample time, due to their internal pre-processing.

Question-4: Pig Query

Note: To run a pig query and make a time comparison, we can simply put:

```
time pig -x local sample.pig
```

The scripts that were used for querying are their in the **Q4 directory**.

The output from the pig query is there in the output directory

Query 1: CGPA Calculation per Student

Objective:

Calculate the CGPA for each student along with their total credits completed using the institutional grading system.

Steps and Logic:

1. Loading Data:

- Load `enrollment.csv` into `enrollment_data` and drop the header row.
- Load `grade.csv` into `grade_roster` and filter out its header row.
- Load `attendance.csv` and `fact_table_final1.csv` similarly, ensuring that header rows are filtered out.

2. Joining Datasets:

- Join `grade_roster` and `fact_table` on matching student and course identifiers (i.e. `student_id` with `member_id` and `subject_code_name` with `course`).

3. Calculating Weighted Points:

- Use a `CASE` expression within a `FOREACH` to calculate the weighted points for each course based on the letter grade (e.g., 'A' as 4.0, 'A-' as 3.7, etc.) multiplied by the course credit.

4. Grouping and Aggregation:

- Group the resulting data by `student_id` to aggregate values.
- Compute the total credits by summing `course_credit` and the total weighted points.
- Calculate the CGPA as the ratio of total weighted points to total credits.

5. Ordering and Storing:

- Order the results by CGPA (in descending order) and by total credits completed.
- Dump and store the output using PigStorage into the `/output/Query-1` directory.

Pig Script Excerpt:

```
-- Join grade_roster and fact_table
joined_data = JOIN grade_roster BY (student_id, subject_code_name),
```

```
fact_table BY (member_id, course);

-- Calculate weighted points
cgpa_data = FOREACH joined_data GENERATE
  grade_roster::student_id AS student_id,
  grade_roster::course_credit AS course_credit,
  (CASE grade_roster::obtained_marks_grade
    WHEN 'A' THEN 4.0 * grade_roster::course_credit
    WHEN 'A-' THEN 3.7 * grade_roster::course_credit
    WHEN 'B+' THEN 3.4 * grade_roster::course_credit
    WHEN 'B' THEN 3.0 * grade_roster::course_credit
    WHEN 'B-' THEN 2.7 * grade_roster::course_credit
    WHEN 'C+' THEN 2.4 * grade_roster::course_credit
    WHEN 'C' THEN 2.0 * grade_roster::course_credit
    WHEN 'D' THEN 1.7 * grade_roster::course_credit
    ELSE 0.0
  END) AS weighted_points;

-- Group and compute totals and CGPA
grouped_data = GROUP cgpa_data BY student_id;
result = FOREACH grouped_data {
  total_credits = SUM(cgpa_data.course_credit);
  total_weighted_points = SUM(cgpa_data.weighted_points);
  cgpa = total_weighted_points / total_credits;
  GENERATE group AS student_id, total_credits AS total_credits_completed,
  cgpa AS cgpa;
}
ordered_result = ORDER result BY cgpa DESC, total_credits_completed DESC;

DUMP ordered_result;
STORE ordered_result INTO '/output/Query-1' USING PigStorage(',');
```

Image

```
(6451f1fdbfb51e85c217fc58523ac177fe9c1e59b0dd11cf65d47035fdb720b1,28,2.3785714285714286)
(b0026ddcb2635476e72f335b7ded6341ede34eb5f8f3e2ed34aa60062d3934fd,32,2.375)
(01021eb63ad8ca36d35a6fd4ead1a931e4dc4b74999a5cf98c7900d8540c97ae,8,2.35)
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(8777036516faed4eabf100af059a4c3e157ceaea6bcdafa28191d593415f64204,28,2.157142857142857)
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(cae5018bebe2ccff689e80a84c44d7d3a6acad9949e72e364e03c5e6116b9bed,32,2.1)
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(1d26c5cdc02e2b8d9ea7983ca28faf91d58e2755852f9ff5d2321a18e21d3b49,4,2.0)
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(08aa713e1d2c465191d99525020cf07f773e107a506a44229e7fffb500ef9d8dd,26,1.623076923076923)
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(99f22d27d8c07ad9de06b443582e2346c5fddcfb9b3b55ab03e562a5c0c4c158a,28,1.4928571428571427)
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(df8239ca5372ac918ccc321ea281f93ca096766e88f3783471b81c7edc720b63,28,1.3071428571428572)
(41a9ffb21135b6c0a3007931bdf1ec944ab4434f1435924a008aa9e3a3ec15f,26,1.2769230769230768)
(9bb1f24866e6e0ab55847f85f87829cd4f7be72d1d341c9e514f14602e4e30d4,28,1.2642857142857142)
(075f4288380a972f084731c23f3ae382165107e4c5a2a2cd85363d3a96046fed,24,1.1333333333333333)
(e03396384ee196698bfc8bc0e21b2af1f2d72950c2d505a6be57261f1a2b6634,28,1.0357142857142858)
(84c39a5f9e43f9068fb7d4de358f0bbf67c90947463da8fe264c40c6895502e6,22,0.890909090909091)
(5e66c5f5200f0426105d3639378ede436e1b0611b183df366fd42b5b4b3e7bac,28,0.5785714285714285)
(9582fbc05cf3288085a5d745452ceb2255674776c23c0495cd6d6e852418a02,28,0.5285714285714286)
(7fd5a24c7f7cae6655cc5747682409abc28f5872fdd868bb033310ab07b1fa0c,24,0.0)
(14c1e6fdb35fc08eb0fe6b496924fdb2280c15bb2ab9279e4ca9d4c8d73a4e2,20,0.0)
(746fbb665bfd41bf0470020cf596bea17d648b383f88f991408c55c191059b59,8,0.0)
(56a2e07bec0c4250925b2bb8579ac06a309404e9d03d911627b986a2f8ad57a7,8,0.0)
2025-04-14 23:43:35,602 [main] INFO org.apache.pig.Main - Pig script completed in 5 seconds and 5 milliseconds (5005 ms)

real    0m6.705s
user    0m17.949s
sys     0m1.493s
python3 hadoop2/hadoop2/hadoop2-#B-Pwd315e-testes-44-cd1-py3 /D:/hadoop/.../3/046
```

Elapsed time:5.005 seconds

Query 2: Faculty-wise Summary of Attendance and Course Credit

Objective:

Calculate the number of students, average attendance percentage, and maximum course credit for each faculty by filtering for passed students.

Steps and Logic:

1. Joining Datasets:

- Join the **fact_table** and **grade_roster** on student and course identifiers.

2. Filtering:

- Filter the joined dataset for records where the exam result is **'Pass'** to focus on successful outcomes.

3. Grouping by Faculty:

- Group the filtered records by **faculty_name**.

4. Aggregation:

- Count distinct students per faculty.

- Compute the average attendance using the `average_attendance_percent` from the fact table.
- Determine the maximum course credit awarded for courses taught by each faculty.

5. Output:

- Dump the results and store them into `/output/Query-2`.

Pig Script Excerpt:

```
-- Join fact_table and grade_roster
joined_data = JOIN fact_table BY (member_id, course), grade_roster BY
(student_id, subject_code_name);

-- Filter for students who passed
filtered_data = FILTER joined_data BY grade_roster::exam_result == 'Pass';

-- Group by faculty_name and compute aggregates
grouped_data = GROUP filtered_data BY grade_roster::faculty_name;
result = FOREACH grouped_data {
    unique_students = DISTINCT filtered_data.grade_roster::student_id;
    GENERATE group AS faculty_name,
              COUNT(unique_students) AS num_students,
              AVG(filtered_data.fact_table::average_attendance_percent) AS
avg_attendance,
              MAX(filtered_data.grade_roster::course_credit) AS
max_course_credit;
}

DUMP result;
STORE result INTO '/output/Query-2' USING PigStorage(',');
```


Image

```

2025-04-14 23:53:13.086 [main] WARN org.apache.pig.backend.hadoop.executionengine.mapReduceLayer.MapReduceLauncher - Encountered Warning ACCESSING_NON_EXISTENT_FIELD 30 tti
2025-04-14 23:53:13.086 [main] WARN org.apache.pig.backend.hadoop.executionengine.mapReduceLayer.MapReduceLauncher - Encountered Warning FIELD_DISCARDED_TYPE_CONVERSION_FAIL
s).
2025-04-14 23:53:13.086 [main] INFO org.apache.pig.backend.hadoop.executionengine.mapReduceLayer.MapReduceLauncher - Success!
2025-04-14 23:53:13.089 [main] WARN org.apache.pig.data.SchemaTupleBackend - SchemaTupleBackend has already been initialized
2025-04-14 23:53:13.091 [main] INFO org.apache.hadoop.mapreduce.lib.input.FileInputFormat - Total input files to process : 1
2025-04-14 23:53:13.091 [main] INFO org.apache.pig.backend.hadoop.executionengine.util.MapRedUtil - Total input paths to process : 1
(Vinu E V,59,87.05762688588288,4)
(V Sridhar,313,83.28612771888689,4)
(S Malapaka,166,80.00903669610081,4)
(Sachit Rao,150,74.71743122415805,4)
(Tulika Saha,120,73.93666648864746,2)
(Uttam Kumar,2,28.0,4)
(Vinod Reddy,5,67.04000091552734,4)
(Viswanath G,145,85.38620755425815,4)
(Nanditha Rao,42,66.87857182820638,4)
(Priyanka Das,6,77.18333371480306,4)
(Sakshi Arora,30,73.76666717529297,4)
(Thangaraju B,149,92.32364866218052,4)
(Jyotsna Bapat,2,97.20000076293945,4)
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(Srinivas Vivek,198,77.55353602014407,4)
(Sushree Behera,4,81.82500076293945,4)
(Kurian Polachan,91,86.91978018624442,4)
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(Ashish Choudhury,6,80.73333358764648,4)
(Manisha Kulkarni,119,76.56722676253118,4)
(Meenakshi D Souza,3,86.26666514078777,4)
(Srinath Srinivasa,3,88.9000015258789,4)
(Amit Chattopadhyay,159,84.39371070621898,4)
(Prof. Amrita Mishra,120,79.95333296457926,4)
(Badrinath Ramamurthy,120,87.22250073750814,2)
(G Srinivasa Raghavan,4,88.67499923706055,4)
(Jaya Sreevalsan Nair,1,70.80000305175781,4)
(Pillalamarri Sridhar,160,80.70999963283539,4)
(Sujit Kumar Chakrabarti,160,86.43625028133393,2)
(Karthikeyan Vaidyanathan,1,85.69999694824219,4)
2025-04-14 23:53:13.136 [main] INFO org.apache.pig.Main - Pig script completed in 4 seconds and 445 milliseconds (4445 ms)

real    0m6.143s
user    0m15.457s
sys     0m1.430s

```

Elapsed time:4.445 seconds

Query 3: Identify Low Attendance (Below 75%) per Student-Course

Objective:

Determine the attendance percentage for each student in each course and identify those records where attendance is below 75%.

Steps and Logic:

1. Joining Datasets:

- Join **fact_table** with **grade_roster** on matching student and course identifiers.

2. Grouping Data:

- Group the joined data by both **student_id** and **subject_code_name** to work at the granularity of each student's course.

3. Attendance Calculation:

- Compute total classes attended and absent for each group.
- Calculate the overall attendance percentage using the formula:

$$(\text{attendance_percentage}) = \frac{\text{total attended}}{\text{total attended} + \text{total absent}} \times 100$$

4. Filtering:

- Filter out groups where the attendance percentage is less than 75%.

5. Output:

- Dump and store the final filtered output into **/output/Query-3**.

Pig Script Excerpt:

```
-- Join fact_table and grade_roster
joined_data = JOIN fact_table BY (member_id, course), grade_roster BY
(student_id, subject_code_name);

-- Group by student_id and subject_code_name
grouped_data = GROUP joined_data BY (grade_roster::student_id,
grade_roster::subject_code_name);

-- Calculate attendance metrics per group
attendance_data = FOREACH grouped_data {
    total_attended =
SUM(joined_data.fact_table::number_of_classes_attended);
    total_absent = SUM(joined_data.fact_table::number_of_classes_absent);
    attendance_percentage = (total_attended * 100.0) / (total_attended +
total_absent);
    GENERATE FLATTEN(group) AS (student_id, course),
        total_attended AS total_classes_attended,
        total_absent AS total_classes_absent,
        attendance_percentage AS overall_attendance_percentage;
}

-- Filter groups with attendance below 75%
filtered_attendance = FILTER attendance_data BY
overall_attendance_percentage < 75;

DUMP filtered_attendance;
STORE filtered_attendance INTO '/output/Query-3' USING PigStorage(',');
```

Image

```
(f9746d5926e1ef8be988f4a01b8897189476a4792deee63c7aa37e2d31b862a3,EGC 112/Programming 1B (Python Programming),8,4,66.66666666666667)
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(fbd0443bf1e0d231601b6aff94a29877222acac5946506425863c35151df2084,GNL 101/English,5,5,50.0)
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(fc43072bf0449e0f4f3743a9fb44d63507c0444bf6db7440443111fb0f406bce,HSS 111/Economics-1,7,6,53.84615384615385)
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(fdb1bf0b3ff8d8048103388f108794de4164bbe8dbdf7d898a6036965cc2f292,GNL 101/English,7,4,63.63636363636363)
(fdb1bf0b3ff8d8048103388f108794de4164bbe8dbdf7d898a6036965cc2f292,AMS 103/Calculus,92,40,69.6969696969697)
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2025-04-14 23:54:24,976 [main] INFO org.apache.pig.Main - Pig script completed in 4 seconds and 536 milliseconds (4536 ms)
```

```
real    0m6.261s
user    0m16.118s
sys      0m1.387s
```

Elapsed time:4.536 seconds

Comparison of Hive vs. Pig

Table 1: Comparison of HiveQL Query Execution and Pig Query Execution

Query	Hive Without Bucketing(seconds)	Hive With Bucketing (seconds)	Pig performance (seconds)
Query 1	6.54	1.643	5.005
Query 2	0.912	0.793	4.445
Query 3	1.23	1.018	4.536

1. Installation & Setup

- **Hive:**
 - Typically involves setting up a Hive metastore along with Hadoop.
 - More components (HiveServer2, Metastore, etc.) need to be configured.
 - Can be complex to install and manage, especially in a production environment.
- **Pig:**
 - Generally easier to install and lightweight.
 - Runs as a single script without the need for a separate metastore.
 - Quick to set up on local mode or within a Hadoop cluster.

2. Query Language & Ease of Writing

- **Hive:**
 - Uses a SQL-like language (HiveQL) that is familiar to users with a relational database background.
 - Declarative queries make it easier for those accustomed to SQL.
 - Built-in functions and windowing can make complex queries simpler.
- **Pig:**
 - Uses a scripting language called Pig Latin, which is procedural.
 - Offers more flexibility and control when writing data transformation logic.
 - Can be easier for iterative data processing tasks, but may require more lines of code for similar SQL operations.

3. Query Performance & Optimization

- **Hive:**
 - Optimized for complex, long-running queries over large datasets.
 - Supports indexing, partitioning, and bucketing, which can significantly improve query performance when properly tuned.
 - More suitable for batch processing analytical queries.
- **Pig:**
 - Also handles large datasets but can be more efficient for ETL tasks and transformations.
 - Performance can be comparable to Hive for many transformation operations; however, highly optimized **Hive queries may outperform Pig on complex aggregations.**
 - Less emphasis on indexing and more on user-defined optimizations via scripting logic.

4. Suitability & Use Cases

- **Hive:**

- Best suited for analysts comfortable with SQL.
- Ideal for ad hoc queries and reporting where the data schema is well-defined.
- Strong integration with BI tools and reporting systems.
- **Pig:**
 - Excellent for ETL workflows and data processing pipelines.
 - Preferred when you need fine-grained control over data transformations.
 - Often used in scenarios where rapid prototyping of data flows is required.

5. Community & Ecosystem

- **Hive:**
 - Widely adopted in enterprises, with robust community support and integration with many Hadoop components.
 - Part of the broader SQL-on-Hadoop ecosystem.
- **Pig:**
 - Once very popular for data processing tasks, but usage has decreased in favor of Spark and other processing frameworks.
 - Still a viable option for specific transformation-heavy workflows.

In the table as well, we can see that Hive outperforms Pig on almost all queries in terms of time, and when Hive is optimised with partitioning and bucketing, it always outperforms Pig.

Also, it was a little difficult to write pig scripts since it is easier to write SQL statements, which is similar to Hive queries.