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
- 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	
6451f1fdbfb51e85c217fc58523ac177fe9c1e59b0dd11cf65d47035fdb720b1		2.3785714285714286	
b0026ddcb2635476e72f335b7ded6341ede34eb5f8f3e2ed34aa60062d3934fd	32.0	2.375	
01021eb63ad8ca36d35a6fd4ead1a931e4dc4b74999a5cf98c7900d8540c97ae	8.0	2.35	
5db0ea3e96305d5b2434e0a9e3657a76c67509c8327c7e47fd54d1b4b9063f31	26.0	2.3307692307692305	
4caf9268ea5658127bf8512445be6922eec2357c8c52b5c5a2c631cae6af0c5d	22.0	2.290909090909091	
86b2b4629113bb3a78373aa25f95a8dcc6e5676327b2c3e36109872ac9bacc2c	12.0	2.26666666666667	
447f6ae3c7fd293dabbad856074c77f5ac90b133b9b114cc8080e78770d60882	22.0	2.25454545454544	
ad841dec8c5b2f1952dc51dd68adf513a672c4ddeaf228935127ce06c875c20a	22.0	2.2363636363636363	
c4ff6797d1fb4433553653d82b0289c32a3c7837c7012da48ecab2ac9c01ee3a	32.0	2.1875	
8777036516faed4eabf100af059a4c3e157ceaea6bcdfa28191d593415f64204	28.0	2.157142857142857	
46afcb932a74d834d21d0547dee5b8bfefa616f4049b3b77dd47c045c2101cc9		2.1	
cae5018bebe2ccff689e80a84c44d7d3a6acad9949e72e364e03c5e6116b9bed		2.1	
19c5c74b92596d69c552ea81c9aab4370c91a8753e1b64020a7cf16367ea3ea1	26.0	2.0615384615384613	
g.student_id total_credi	ts_completed	cgpa	
+			
b7f97c4154f2b34129c7f5192e1c40e1436ec1f742924fddb0c19252dc5a15bb		2.025	
9886071454e243de3f7fcd672bc754d453b29a5f08e6c6e0df0c5cf8b47f4362		2.0	
1d26c5cdc02e2b8d9ea7983ca28faf91d58e2755852f9ff5d2321a18e21d3b49		2.0	
1b5b60677927228f94b20a68dadf069e43e687a6ebeaebb81cff935eeeab4f67		1.807142857142857	
8177fca161b90d83cee14b5e9162f828670d8035a199b48bb5110432b623e9a7		1.7363636363636	
d24d0df17e3bbea38e89f2eda4c03d9b30c756f4fa6aeba9ff7e3f8cb7e78bc4		1.6846153846153844	
08aa713e1d2c465191d99525020cf07f773e107a506a44229e7ffb500efd98dd		1.6230769230769229	
2b6a85597239bfe683c37419733fb3a9db6d8c4abfd93fa6db9db6f3bca9d493		1.599999999999999	
99f22d27d8c07ad9de06b443582e2346c5fdcfb9b3b55ab03e562a5c0c4c158a		1.4928571428571427	
fd9709ae2b08802a0cfc32aa1971dd29c0de7c8b4be3cc07a1cb968fe2405ed5		1.4785714285714284	
882faaed944cce28b59a882b46075b76dad00b0580d3012800a19a25ae9b3221		1.400000000000001	
3a2e34b3ebca5885323eb7b26d74eab2436cab04d22897c099635d550c9e9201		1.3090909090909	
df8239ca5372ac918ccc321ea281f93ca096766e88f3783471b81c7edc720b63		1.307142857142857	
41a9ffb21135b6c0a3007931bdfe1ec944ab4434f1435924a008aa9e3a3ec15f		1.2769230769230768	
9bb1f24866e6e0ab55847f85f87829cd4f7be72d1d341c9e514f14602e4e30d4 075f4288380a972f084731c23f3ae382165107e4c5a2a2cd85363d3a96046fed		1.2642857142857142 1.133333333333333333333333333333333333	
e03396384ee196698bfc8bc0e21b2af1f2d72950c2d505a6be57261f1a2b6634		1.133333333333333	
84c39a5f9e43f9068fb7d4de358f0bbf67c90947463da8fe264c40c6895502e6		1.035/14285/142858	
5e66c5f5200f0426105d3639378ede436e1b0611b183df366fd42b5b4b3e7bac		0.8909090909091	
9582fbc05cf3288085a5d745452cebc2255674776c23c0495cdbd6e852418a02		0.5285714285714286	
7fd5a24c7f7cae6655cc5747682409abc28f5872ffd868bb033310ab07b1fa0c		0.5285/14285/14286	
14c1e6f6db35fc08eb0fe6b496924fdb2280c15bb2ab9279e4ca9d4c8d73a4e2		0.0	
14C1e016db331C88eb01e0b4969241db2286C13bb2ab3279e4Ca3d4C8d7364e2		0.0	
746fbb665bfd41bf0470020cf596bea17d648b383f88f991408c55c191059b59		1 0.0	
+		+	
524 rows selected (1.043 seconds)			
0: idbc:hive2://localhost:10000/>			
0. idharbinaa //larabaa 10000 /		·	<u> </u>

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.

Priyanka Das 6 77.1833333333335 4.0
Priyanka Das 6 77.1833333333335 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 88.9000000000000000 4.0 Srinitvas Vivek 198 77.5535353535357 4.0 Sujit Kumar Chakrabrati 160 86.43624999999997 2.0 Sushree Behera 4 81.825 4.0 Thangaraju B 149 92.32364864864864 4.0 Tulika Saha 120 73.936666666666666667 2.0
Prof. Amrita Mishra 120 79.9533333333333333333333333333333333333
S Malapaka 166 80.00903614457827 4.0 Sachti Rao 150 74.71743119266957 4.0 Sakshi Arora 30 73.76666666666667 4.0 Srinath Srinivasa 3 88.900000000000000 4.0 Srinivas Vivek 198 77.55353535353527 4.0 Sujir Kumar Chakrabrati 160 86.43624999999997 2.0 Sushree Behera 4 81.825 4.0 Thangaraju B 149 92.32364864864864 4.0 Tulika Saha 120 73.936666666666667 2.0
Sachit Rao 150 74.71743119266057 4.0 Sakshi Arora 30 73.76666666666667 4.0 Srinath Srinivasa 3 88.90000000000000000 4.0 Srintvas Vivek 198 77.553535353535327 4.0 Sujit Kumar Chakrabrati 160 86.43624999999997 2.0 Sushree Behera 4 81.825 4.0 Thangaraju B 149 92.32364864864864 4.0 Tulika Saha 120 73.936666666666667 2.0
Sakshi Arora 30 73.76666666666667 4.0 Srinath Srinivasa 3 88.90000000000002 4.0 Srinivas Vivek 198 177.553535353535353535353535353527 4.0 Sujit Kumar Chakrabrati 160 86.4362499999997 2.0 Sushree Behera 4 81.825 4.0 Thangaraju B 149 92.32364864864864 4.0 Tulika Saha 120 73.936666666666667 2.0
Srinath Srinivasa 3 88.90000000000002 4.0 Srinivas Vivek 198 77.55353535353527 4.0 Sujit Kumar Chakrabrati 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
Srinivas Vivek 198 77.55353535353527 4.0 Sujit Kumar Chakrabrati 160 86.43624999999997 2.0 Sushree Behera 4 81.825 4.0 Thangaraju B 149 92.32364864864864 4.0 Tulika Saha 120 73.936666666666667 2.0
Sujit Kumar Chakrabrati 160 86.43624999999997 2.0 Sushree Behera 4 81.825 4.0 Thangaraju B 149 92.323364864864864 4.0 Tulika Saha 120 73.936666666666667 2.0
Sushree Behera 4 81.825 4.0 Thangaraju B 149 92.32364864864864 4.0 Tulika Saha 120 73.936666666666667 2.0
Thangaraju B 149 92.3236486486464 4.0 Tulika Saha 120 73.9366666666667 2.0
Tulika Saha 120 73.9366666666667 2.0
Uttam Kumar 2 28.0 4.0
V Sridhar 313 83.2861271676299 4.0
Vinod Reddy 5 67.039999999999 4.0
Vinu E V 59 87.05762711864405 4.0
Viswanath G 145 85.38620689655166 4.0
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 6363	EGC 112/Programming 1B (Python Programming)	7.0	4.0	63.63636363
fdb1bf0b3ff8d8048103388f108794de4164bbe8bdbf7d898a6036965cc2f292	AMS 101/Probability & Statistics	68.0	32.0	68.0
 fdb1bf0b3ff8d8048103388f108794de4164bbe8bdbf7d898a6036965cc2f292	AMS 103/Calculus	92.0	40.0	69.69696969
97 fdb1bf0b3ff8d8048103388f108794de4164bbe8bdbf7d898a6036965cc2f292	EGC 102/Digital Design	25.0	9.0	73.52941176
 fdb1bf0b3ff8d8048103388f108794de4164bbe8bdbf7d898a6036965cc2f292	EGC 112/Programming 1B (Python Programming)	7.0	4.0	63.63636363
363 fdb1bf0b3ff8d8048103388f108794de4164bbe8bdbf7d898a6036965cc2f292	GNL 101/English	7.0	4.0	63.63636363
363 fe6cacdcebbf5892a3583e6ec13530f2e6ea7c6c75a90fcced9a2645e7200033	AMS 101/Probability & Statistics	40.0	28.0	58.82352941
.47 fe6cacdcebbf5892a3583e6ec13530f2e6ea7c6c75a90fcced9a2645e7200033	AMS 103/Calculus	48.0	56.0	46.15384615
615 fe6cacdcebbf5892a3583e6ec13530f2e6ea7c6c75a90fcced9a2645e7200033	EGC 102/Digital Design	17.0	10.0	62.96296296
296 fe6cacdcebbf5892a3583e6ec13530f2e6ea7c6c75a90fcced9a2645e7200033	GNL 101/English	0.0	1.0	0.0
 fe6cacdcebbf5892a3583e6ec13530f2e6ea7c6c75a90fcced9a2645e7200033	HSS 111/Economics-1	2.0	10.0	16.6666666
6668 fedafcd150b9a17932760554a0ec9208266957a49da49214f4f9c7e1776f340d	GNL 101/English	7.0	3.0	70.0
 ff6358e8fa8dce631d81990d463738796e3eb5cb545a29edad662cd92864cbfb	VLS 505/System design with FPGA	6.0	3.0	66.6666666
667 ffba274d8a68b64e86980a5d807a0057faa389d2c7a5857424d47dc960e8c434	AIM 511/Machine Learning	0.0	4.0	0.0
 ffe3d002fbf6b6c4020303b73c54bcef8c8e9c4b5db7108ac2c8f9b206f0f177	EGC 111/Programming 1A (C Programming)	32.0	28.0	53.33333333
3336 ffe3d002fbf6b6c4020303b73c54bcef8c8e9c4b5db7108ac2c8f9b206f0f177 	GNL 101/English	7.0	3.0	70.0

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.