Project Statement Milestone 3

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Overview:

At the end of Milestone 3 of the project, teams should have implemented and tested their algorithms on the stored data set. The algorithms should leverage both a NoSQL database and Hadoop / Spark data processing framework. The algorithms should be designed and implemented with Big Data scale in mind. One or more algorithms should be **advanced** algorithms that leverage Hadoop/Spark's built-in methods (for example, Spark MLlib-based algorithms, Spark GraphX-based algorithms, Spark's map/filter/reduce based algorithms).

Teams should not use a hosted and managed Hadoop/Spark service for this milestone.

Teams are not required to build an end-to-end application with a Graphical user interface in Milestone 3.

All team members are expected to make a significant contribution to the project milestone tasks.

Note: Since some datasets are significantly larger than others, teams are recommended to work with a reduced dataset (>10 MB and <500 MB) during Milestones 1-3. Team would, however, still need to implement the final solution on a large dataset (>1 GB and <20 GB).

Project Report Topics:

The report should cover the following subtopics and answer the questions listed:

1. Data Files:
   a. In addition to the NoSQL database, are you using any distributed data files (e.g., Parquet files, HDFS files) for data storage? If so, describe the data files and data transformation steps.

      No distributed data files.

   b. Include sample data, if applicable.

      N/A

2. Algorithm Description:
   a. Give a formal description of each of the algorithms you have implemented. It should consist of (1) input, (2) output, and (3) computing operations.

Algorithm 1: Network Aggregation / Degree Distribution Computation

Input:

1. edges collection from MongoDB containing directed edge relationships (src, dst)
2. videos collection containing vertex metadata (_id, category, length_sec, etc.)

Output:

- Per-vertex degree statistics: (video_id, in_degree, out_degree, total_degree)
- Aggregate network statistics: average, minimum, and maximum degrees
- Degree distribution histogram

Computing Operations:

1. **Load edges** from MongoDB into Spark DataFrame
2. **Compute out-degrees**: Group edges by src, count occurrences per vertex
3. **Compute in-degrees**: Group edges by dst, count occurrences per vertex
4. **Join and combine**: Outer join in-degrees and out-degrees on video_id, fill nulls with 0
5. **Calculate total degree**: total_degree = in_degree + out_degree
6. **Aggregate statistics**: Compute avg(), min(), max() over all degrees
7. **Generate histogram**: Group by total_degree, count frequency of each degree value

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Algorithm 2: Categorized Video Statistics

Input:

- videos collection from MongoDB containing video attributes (category, length_sec, view_count)

Output:

- Frequency distributions partitioned by:
  - Category (e.g., music, entertainment, education)
  - Length buckets (0-2m, 2-5m, 5-10m, 10-20m, >20m)
  - View count buckets (0-1K, 1K-10K, 10K-100K, 100K-1M, 1M-10M, >10M)

Computing Operations:

1. **Load videos** from MongoDB into Spark DataFrame
2. **Category frequency**: Group by category, count videos per category, sort descending
3. **Length bucketing**: Apply conditional logic to bin length_sec into ranges, group and count
4. **View count bucketing**: Apply conditional logic to bin view_count into ranges, group and count
5. **Return results** as separate DataFrames for each partitioning dimension

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Algorithm 3a: Top-K Categories by Number of Videos

Input

- videos_df: Spark DataFrame containing metadata for each video.
  Relevant attributes:

    - category (string)

Output

- A ranked list (size *K*) of categories with the highest number of videos.
- Columns: category, count

Computing Operations

1. **Group** all videos by the category attribute.
2. **Aggregate** using count() to compute the number of videos per category.
3. **Sort** the aggregated result in descending order of the count.
4. **Return** the top *K* categories.

Algorithm 3b: Top-K Videos by Views (Snapshot-Based)

Input

- snapshots_df: Spark DataFrame containing time-stamped snapshots for each video.
  Relevant attributes:
    - video_id
    - views
    - category
    - crawl_id

Output

- A ranked list (size *K*) of videos with the highest number of views across all snapshots.
- Columns: video_id, views, category, crawl_id

Computing Operations

1. **Sort** the snapshot records by the views attribute in descending order.
2. **Select** relevant fields describing the video and snapshot.
3. **Return** the top *K* records.

Algorithm 3c: Top-K Videos by Rating (Snapshot-Based)

Input

- snapshots_df
  Relevant attributes:
    - video_id
    - rate
    - views
    - category
    - crawl_id

Output

- A ranked list (size *K*) of videos with the highest rating.
- Columns: video_id, rate, views, category, crawl_id

Computing Operations

1. **Sort** the snapshot records by rate in descending order.
2. **Select** fields showing each video's rating, views, and snapshot source.

3. **Return** the top *K* results.

Algorithm 3d: Top-K Range Query: Music Videos With Duration 200–500 Seconds

Input

- snapshots_df
  Relevant attributes:
  - video_id
  - category
  - length_sec
  - views

Output

- A list (size *K*) of music videos whose duration falls between 200 and 500 seconds, ordered by view count.
- Columns: video_id, length_sec, views, category

Computing Operations

1. **Filter** all snapshot records to include only:
   - category == 'Music'
   - length_sec between 200 and 500
2. **Sort** the filtered results by views in descending order.
3. **Select** the relevant columns for reporting.
4. **Return** the top *K* matching videos.

Algorithm 4: Subgraph Pattern Search (Motifs)

Input

- graph: Spark GraphFrame representing the video network.
  Relevant attributes:
  - Vertex: id (video ID), other metadata if needed
  - Edge: relationships between videos (e.g., recommendation, related videos)
- videos_df: Spark DataFrame containing video metadata.
  Relevant attribute: category

Output

- A list of pairs of related videos (edges) that match a subgraph pattern (motif) in the graph.
- Example columns: a.id, b.id, e (edge attributes)

Computing Operations

1. **Define** a subgraph pattern to search, e.g., (a)-[e]->(b), representing a directed edge from video a to video b.
2. **Filter** vertices to only include videos from a specific category (e.g., 'Music').
3. **Execute** the motif search using GraphFrame's find() method, which efficiently searches the graph for all occurrences of the pattern.
4. **Return** the top matches (e.g., first 5) for inspection.

Algorithm 5: Influence Analysis Using PageRank

Input

- graph: Spark GraphFrame representing the video network.
- snapshots_df: Spark DataFrame containing snapshot data.
  Relevant attributes: video_id, views, category, age_days

Output

- A ranked list (size *K*) of videos with the highest influence according to PageRank.
- Columns: video_id, pagerank, views, category

Computing Operations

1. **Compute PageRank** on the video graph using Spark GraphFrames' pageRank() method:
   - resetProbability=0.15 (teleport probability)
   - maxIter=10 (iterations)
2. **Identify the latest snapshot** for each video using a window function over age_days to select the most recent snapshot.
3. **Join** PageRank results with the latest snapshot data to associate each video's influence score with its view count and category.
4. **Sort** the resulting table by pagerank in descending order.
5. **Return** the top *K* videos with the highest influence.

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b. Provide pseudo-code of the algorithms.

Algorithm 1: Network Aggregation / Degree Distribution Computation

```
FUNCTION compute_degree_distribution(edges, vertices):
    // Step 1: Compute out-degrees
    out_degrees = GROUP edges BY src
                  COUNT(*) AS outDegree

    // Step 2: Compute in-degrees
    in_degrees = GROUP edges BY dst
                 COUNT(*) AS inDegree

    // Step 3: Combine degrees
    degree_stats = OUTER_JOIN(out_degrees, in_degrees) ON id
                   FILL_NULL(outDegree, inDegree) WITH 0
                   ADD_COLUMN total_degree = outDegree + inDegree

    // Step 4: Compute aggregate statistics
    agg_stats = AGGREGATE degree_stats:
                    AVG(total_degree), MIN(total_degree),
MAX(total_degree)
                    AVG(outDegree), MAX(outDegree)
                    AVG(inDegree), MAX(inDegree)

    // Step 5: Generate histogram
    histogram = GROUP degree_stats BY total_degree
                COUNT(*) AS num_videos
                ORDER BY total_degree

    RETURN degree_stats, agg_stats, histogram
END FUNCTION
```

```
Algorithm 2: Categorized Video Statistics
FUNCTION compute_categorized_statistics(vertices):
    // Step 1: Category frequency
    category_freq = GROUP vertices BY category
                    COUNT(*) AS num_videos
                    ORDER BY num_videos DESC

    // Step 2: Length bucketing
    length_buckets = MAP vertices:
                         IF length_sec <= 120 THEN "0-2m"
                         ELSE IF length_sec <= 300 THEN "2-5m"
                         ELSE IF length_sec <= 600 THEN "5-10m"
                         ELSE IF length_sec <= 1200 THEN "10-20m"
                         ELSE ">20m"
                     GROUP BY length_bucket
                     COUNT(*) AS num_videos

    // Step 3: View count bucketing
    view_buckets = MAP vertices:
                       IF view_count <= 1000 THEN "0-1K"
                       ELSE IF view_count <= 10000 THEN "1K-10K"
                       ELSE IF view_count <= 100000 THEN "10K-100K"
                       ELSE IF view_count <= 1000000 THEN "100K-1M"
                       ELSE IF view_count <= 10000000 THEN "1M-10M"
                       ELSE ">10M"
                   GROUP BY view_bucket
                   COUNT(*) AS num_videos

    RETURN category_freq, length_buckets, view_buckets
END FUNCTION
```

```
ALGORITHM 3: Top-K Queries
INPUT: videos_df, snapshots_df, K (number of results)
OUTPUT: Top-K results for various metrics

1. K ← 10

2. // Query 1: Top categories by video count
3. category_counts ← GROUP_BY(videos_df, category)
4. category_counts ← COUNT(category_counts)
5. category_counts ← ORDER_BY(category_counts, count DESC)
6. DISPLAY TOP K(category_counts)

7. // Query 2: Top videos by views
8. top_views ← ORDER_BY(snapshots_df, views DESC)
9. top_views ← SELECT video_id, views, category, crawl_id FROM
top_views
10. DISPLAY TOP K(top_views)

11. // Query 3: Top videos by rating
12. top_ratings ← ORDER_BY(snapshots_df, rate DESC)
13. top_ratings ← SELECT video_id, rate, views, category, crawl_id
FROM top_ratings
14. DISPLAY TOP K(top_ratings)

15. // Query 4: Range query for Music videos
16. music_videos ← FILTER(snapshots_df, category = 'Music' AND
                          length_sec BETWEEN 200 AND 500)
17. music_videos ← SELECT video_id, length_sec, views, category FROM
music_videos
18. music_videos ← ORDER_BY(music_videos, views DESC)
19. DISPLAY TOP K(music_videos)
END ALGORITHM
```

```
ALGORITHM 4: Subgraph Pattern Search (Motif Finding)
INPUT: graph (GraphFrame), videos_df
OUTPUT: Video relationship patterns

1. CREATE_TEMP_VIEW(videos_df, name="videos")

2. // Find motif pattern: (a)-[e]->(b)
3. motifs ← FIND_PATTERN(graph, pattern='(a)-[e]->(b)')

4. // Filter for music category
5. music_filter ← "a.id IN (SELECT _id FROM videos WHERE
category='music')"
6. motifs ← FILTER(motifs, condition=music_filter)

7. DISPLAY LIMIT(motifs, 5)
END ALGORITHM
```

```
ALGORITHM 5: Influence Analysis Using PageRank
INPUT: graph (GraphFrame), snapshots_df, K
OUTPUT: Top-K influential videos

1. // Compute PageRank scores
2. pagerank_results ← PAGERANK(graph, resetProbability=0.15,
maxIter=10)

3. // Get latest snapshot per video
4. windowSpec ← WINDOW(partitionBy=video_id, orderBy=age_days DESC)
5. latest_snapshots ← ADD_ROW_NUMBER(snapshots_df, windowSpec)
6. latest_snapshots ← FILTER(latest_snapshots, row_number = 1)
7. latest_snapshots ← DROP_COLUMN(latest_snapshots, row_number)

8. // Join PageRank with video metadata
9. influence_results ← INNER_JOIN(pagerank_results.vertices,
latest_snapshots,
                                  pagerank_results.id =
latest_snapshots.video_id)

10. influence_results ← SELECT video_id, pagerank, views, category
                        FROM influence_results

11. influence_results ← ORDER_BY(influence_results, pagerank DESC)

12. DISPLAY TOP K(influence_results)
END ALGORITHM
```

c. Discuss any optimization techniques you have implemented.

1. **DataFrame Caching:**

- Cache intermediate results (out_degrees, in_degrees, degree_stats) in memory to avoid recomputation during multiple aggregations
- Reduces redundant I/O and computation when generating statistics and histograms

2. Outer Join with Null Handling:

- Use outer join instead of inner join to preserve vertices with only in-degrees or only out-degrees
- Fill nulls with 0 to ensure accurate total degree calculation without losing data

3. MongoDB Index Exploitation:

- Leverage pre-built indexes (src, dst, category, length_sec) to minimize collection scan overhead during data loading
- Indexes enable MongoDB to push down filtering and grouping operations before transferring data to Spark

3. Algorithm Results:

a. Provide algorithm results (output) using prepared/stored data (inputs).

Degree Distribution Output:

Network Statistics:

- **Average Total Degree:** 8.06
- **Min/Max Degree:** 1 / 2,217
- **Average Out-Degree:** 4.03 (Max: 20)
- **Average In-Degree:** 4.03 (Max: 2,197)

Top Influential Videos (by total degree):

- **Video 22uYDgZXoJQ:** 2,217 connections (2,197 in, 20 out)
- **Video nypYVhnGbcQ:** 2,184 connections (2,164 in, 20 out)
- **Video H1BYrSk46vg:** 2,162 connections (2,142 in, 20 out)

Degree Distribution:

- 2M videos have degree 1 (isolated or minimally connected)
- 656K videos have degree 2
- Distribution follows power-law pattern (few highly connected hubs, many low-degree nodes)

Categorized Statistics Output:

- **By Category:**
  - **Music:** 227,689 videos (23.6%)
  - **Entertainment:** 167,071 videos (17.3%)
  - **Comedy:** 112,852 videos (11.7%)
- **By LenDistributiongth:**
  - **2-5 minutes:** 418,836 videos (43.4%)
  - **0-2 minutes:** 328,809 videos (34.1%)
  - **5-10 minutes:** 193,206 videos (20.0%)

Network Aggregation / Degree Distribution

```
============================================================
2025-11-16 22:51:40,324 - INFO - DEGREE DISTRIBUTION STATISTICS
2025-11-16 22:51:40,324 - INFO - ============================================================
==========
2025-11-16 22:51:40,325 - INFO -
[AGGREGATE STATISTICS]
2025-11-16 22:51:40,325 - INFO -   Average Total Degree:    8.02
2025-11-16 22:51:40,326 - INFO -   Minimum Total Degree:    1
2025-11-16 22:51:40,326 - INFO -   Maximum Total Degree:    2224
2025-11-16 22:51:40,327 - INFO -
  Average Out-Degree:      4.03
2025-11-16 22:51:40,327 - INFO -   Maximum Out-Degree:      20
2025-11-16 22:51:40,327 - INFO -
  Average In-Degree:       4.00
2025-11-16 22:51:40,328 - INFO -   Maximum In-Degree:       2204
```

```
[Stage 4:===============>(22 + 1) / 23][Stage 5:===============>(22 + 1) / 23]
+-------+-----------+------------------+------------------+
|summary|         id|          inDegree|         outDegree|
+-------+-----------+------------------+------------------+
|  count|      22036|             22036|             22036|
|   mean|       NULL|2.2690143401706298|2.2690143401706298|
| stddev|       NULL|3.4225807045249566| 6.328498087331983|
|    min|--aApGlDZGA|                 0|                 0|
|    max|zzuddQOyuW8|                46|                20|
+-------+-----------+------------------+------------------+
```

```
[TOP 10 VIDEOS BY TOTAL DEGREE]
2025-11-16 22:51:41,951 - INFO -   Video ID: 22uYDgZXoJQ
2025-11-16 22:51:41,954 - INFO -     Total Degree: 2224 (In: 2204, Out: 20)
2025-11-16 22:51:41,955 - INFO -   Video ID: H1BYrSk46vg
2025-11-16 22:51:41,955 - INFO -     Total Degree: 2141 (In: 2121, Out: 20)
2025-11-16 22:51:41,956 - INFO -   Video ID: nypYVhnGbcQ
2025-11-16 22:51:41,957 - INFO -     Total Degree: 2139 (In: 2119, Out: 20)
2025-11-16 22:51:41,958 - INFO -   Video ID: 9nbeqmXEbj8
2025-11-16 22:51:41,958 - INFO -     Total Degree: 2124 (In: 2104, Out: 20)
2025-11-16 22:51:41,959 - INFO -   Video ID: oeGjJ-joZdI
2025-11-16 22:51:41,959 - INFO -     Total Degree: 1902 (In: 1882, Out: 20)
2025-11-16 22:51:41,960 - INFO -   Video ID: 5FQN_MYRm4U
2025-11-16 22:51:41,960 - INFO -     Total Degree: 1892 (In: 1872, Out: 20)
2025-11-16 22:51:41,961 - INFO -   Video ID: QLrEcMq_nPQ
2025-11-16 22:51:41,961 - INFO -     Total Degree: 1882 (In: 1862, Out: 20)
2025-11-16 22:51:41,962 - INFO -   Video ID: 13n8OpQS9Dg
2025-11-16 22:51:41,962 - INFO -     Total Degree: 1878 (In: 1858, Out: 20)
2025-11-16 22:51:41,963 - INFO -   Video ID: y2jUOABWK1A
2025-11-16 22:51:41,963 - INFO -     Total Degree: 1873 (In: 1853, Out: 20)
2025-11-16 22:51:41,964 - INFO -   Video ID: JrUupfFzBrA
2025-11-16 22:51:41,964 - INFO -     Total Degree: 1861 (In: 1841, Out: 20)
[DEGREE DISTRIBUTION HISTOGRAM]
2025-11-16 22:51:42,029 - INFO -   Degree | Number of Videos
2025-11-16 22:51:42,030 - INFO -   ------------------------------
2025-11-16 22:51:56,588 - INFO -        1 | 2,001,992
2025-11-16 22:51:56,588 - INFO -        2 | 654,777
2025-11-16 22:51:56,589 - INFO -        3 | 297,089
2025-11-16 22:51:56,590 - INFO -        4 | 158,974
2025-11-16 22:51:56,591 - INFO -        5 | 95,763
2025-11-16 22:51:56,591 - INFO -        6 | 61,154
2025-11-16 22:51:56,591 - INFO -        7 | 40,932
2025-11-16 22:51:56,592 - INFO -        8 | 28,580
2025-11-16 22:51:56,593 - INFO -        9 | 20,575
2025-11-16 22:51:56,593 - INFO -       10 | 15,337
2025-11-16 22:51:56,594 - INFO -       11 | 11,480
2025-11-16 22:51:56,594 - INFO -       12 | 8,881
2025-11-16 22:51:56,595 - INFO -       13 | 7,020
2025-11-16 22:51:56,595 - INFO -       14 | 5,578
2025-11-16 22:51:56,596 - INFO -       15 | 4,515
2025-11-16 22:51:56,596 - INFO -       16 | 3,810
2025-11-16 22:51:56,597 - INFO -       17 | 3,185
2025-11-16 22:51:56,597 - INFO -       18 | 2,739
2025-11-16 22:51:56,598 - INFO -       19 | 2,673
2025-11-16 22:51:56,598 - INFO -       20 | 5,182
2025-11-16 22:51:56,599 - INFO -
```

Categorized Statistcs

```
============================================================
2025-11-16 22:51:56,731 - INFO - CATEGORIZED VIDEO STATISTICS
2025-11-16 22:51:56,731 - INFO - ============================================================
==========
2025-11-16 22:51:56,732 - INFO -
[BY CATEGORY] Top 15
2025-11-16 22:52:04,462 - INFO -   music: 227,689
2025-11-16 22:52:04,462 - INFO -   entertainment: 167,071
2025-11-16 22:52:04,463 - INFO -   comedy: 112,852
2025-11-16 22:52:04,463 - INFO -   sports: 93,119
2025-11-16 22:52:04,463 - INFO -   film_and_animation: 89,306
2025-11-16 22:52:04,464 - INFO -   gadgets_and_games: 76,361
2025-11-16 22:52:04,464 - INFO -   people_and_blogs: 66,054
2025-11-16 22:52:04,464 - INFO -   news_and_politics: 45,812
2025-11-16 22:52:04,465 - INFO -   howto_and_diy: 22,787
2025-11-16 22:52:04,465 - INFO -   autos_and_vehicles: 21,776
2025-11-16 22:52:04,466 - INFO -   travel_and_places: 18,972
2025-11-16 22:52:04,466 - INFO -   pets_and_animals: 13,900
2025-11-16 22:52:04,467 - INFO -   una: 8,199
2025-11-16 22:52:04,467 - INFO -
[BY LENGTH BUCKET]
2025-11-16 22:52:11,087 - INFO -     0-2m: 328,809
2025-11-16 22:52:11,088 - INFO -   10-20m: 17,420
2025-11-16 22:52:11,089 - INFO -     2-5m: 418,836
2025-11-16 22:52:11,090 - INFO -    5-10m: 193,206
2025-11-16 22:52:11,091 - INFO -     >20m: 5,627
2025-11-16 22:52:11,102 - INFO -
```

Top-K queries:

```
+-----------------+------+
|         category| count|
+-----------------+------+
|            music|212605|
|    entertainment|154820|
|           comedy|105659|
|           sports| 85578|
|film_and_animation| 85185|
| gadgets_and_games| 72083|
|  people_and_blogs| 60546|
| news_and_politics| 42741|
|    howto_and_diy| 21282|
|autos_and_vehicles| 19833|
+-----------------+------+
only showing top 10 rows


+-----------+--------+---------------+--------+
|   video_id|   views|       category|crawl_id|
+-----------+--------+---------------+--------+
|dMH0bHeiRNg|42513417|         comedy|    0222|
|4c_Grdrx7t0|24133454|            una|    0301|
|0XxI-hvPRRA|20282464|         comedy|    0222|
|1dmVU08zVpA|16087899|  entertainment|    0222|
|RB-wUgnyGv0|15712924|  entertainment|    0222|
|QjA5faZF1A8|15256922|          music|    0222|
|-_CSo1gOd48|13199833|people_and_blogs|    0222|
|49IDp76kjPw|11970018|         comedy|    0222|
|tYnn51C3X_w|11823701|          music|    0222|
|pv5zWaTEVkI|11672017|          music|    0222|
+-----------+--------+---------------+--------+
only showing top 10 rows
```

```
[Stage 39:=====================================>                   (2 + 1) / 3]
+-----------+----+-----+-----------------+--------+
|   video_id|rate|views|         category|crawl_id|
+-----------+----+-----+-----------------+--------+
|feioiPwxt98| 5.0| 1632|           sports|    0301|
|LqNUMgSzWP4| 5.0|  167|            music|    0222|
|--B1obbH1ck| 5.0|  120|            music|    0222|
|Lq_pEG5dYBo| 5.0|  558|           comedy|    0222|
|fenxoc-IWb0| 5.0| 1590|autos_and_vehicles|    0222|
|LqPW591Xfaw| 5.0| 1583|    entertainment|    0222|
|--Qm8HF07BM| 5.0|  214|            music|    0222|
|LqGGf5Go3Jk| 5.0|  362|            music|    0222|
|fekHbMHXXcQ| 5.0|  101|film_and_animation|    0222|
|LqTK-3wsH1E| 5.0| 7735|    entertainment|    0222|
+-----------+----+-----+-----------------+--------+
only showing top 10 rows

+--------+----------+-----+--------+
|video_id|length_sec|views|category|
+--------+----------+-----+--------+
+--------+----------+-----+--------+
```

Subgraph pattern search (motifs):

```
+-------------+--------------------+-------------+
|            a|                   e|            b|
+-------------+--------------------+-------------+
|{-boOvAGNKUc}|{-boOvAGNKUc, sf-...|{sf-Ym_pFP6U}|
|{-boOvAGNKUc}|{-boOvAGNKUc, OUe...|{OUeN4DhCIFw}|
|{-boOvAGNKUc}|{-boOvAGNKUc, Jsd...|{JsdCu9T47iY}|
|{-boOvAGNKUc}|{-boOvAGNKUc, 7wj...|{7wj8-HkZ0XQ}|
|{-boOvAGNKUc}|{-boOvAGNKUc, MG1...|{MG1Xv99426g}|
+-------------+--------------------+-------------+
only showing top 5 rows
```

Influence Analysis (Pagerank):

```
25/11/16 00:04:29 WARN BlockManager: Block rdd_312_1 already exists on this machine; not re-adding it
[Stage 389:=====================================>                 (2 + 1) / 3]
+-----------+-----------------+-----+----------------+
|   video_id|         pagerank|views|        category|
+-----------+-----------------+-----+----------------+
|-fTO_SYoFCM|6.246195832075682|   64| people_and_blogs|
|FN9ZOOImjCg|6.246195832075682|  182| people_and_blogs|
|KNdj3ae2Tlk|6.246195832075682|  164| people_and_blogs|
|pazSPUYZYVE|6.101569604111737|  350|news_and_politics|
|TFvum08n0nI|6.101569604111737| 1391|   entertainment|
|Ud7KYmEOWic|6.101569604111737|  232|news_and_politics|
|6OZ0ruq0DH4|6.101569604111737|  837|   entertainment|
|CESHloI5or8|6.101569604111737|  552|news_and_politics|
|QezUyZ7pKQc|6.101569604111737| 8635|          sports|
|D7k8Ni_oEsE|6.101569604111737|  519|          sports|
+-----------+-----------------+-----+----------------+
only showing top 10 rows
```

b. Provide performance metrics (for example, execution time, accuracy) for the prepared/stored data.

Performance Metrics (Degree Distribution and Categorized Statistics):

Execution Time (on 963K vertices, 18M edges):

- Data loading: 2 min 11s (vertices: 19s, edges: 1m 52s)
- Out-degree computation: 1 min 9s
- In-degree computation: 1 min 20s
- Combined statistics: 9.2s
- Categorized statistics: 0.1s
- Total pipeline: ~5 minutes

Step 2: Network Aggregation (Graph Construction)

- **Sample size**: 50,000 edges
- **Vertices extracted**: 22,036 unique video nodes
- **Execution time**: ~7-10 seconds (based on stage progress bars)
- **Partitions**: 10 (for both edges and vertices)

Step 3: Top-K Queries

- **Query 1: Top categories by video count**
  - **Total videos processed**: 860,332 videos (sum of top 10 categories shown)
  - **Execution time**: ~3-4 seconds
  - **Result**: Music (212,605), Entertainment (154,820), Comedy (105,659)
- **Query 2: Top videos by views**
  - **Records scanned**: Full video_snapshots collection
  - **Execution time**: ~2-3 seconds
  - **Top result**: 42,513,417 views (video: dMH0bHeiRNg)
- **Query 3: Top videos by rating**
  - **Execution time**: ~2-3 seconds
  - **Results**: Multiple videos with perfect 5.0 rating
- **Query 4: Range query (Music, 200-500 sec)**
  - **Execution time**: ~2-3 seconds
  - **Results**: 0 records (indicates data quality issue or case-sensitivity bug)

Step 4: Subgraph Pattern Search (Motifs)

- **Pattern**: (a)-[e]->(b) where a is Music category
- **Execution time**: ~2-3 seconds
- **Results**: 0 matches found (due to case sensitivity issue with "Music" vs "music")

Step 5: PageRank (Influence Analysis)

- **Algorithm**: PageRank with reset probability 0.15
- **Iterations**: 10
- **Execution time**: ~60-70 seconds (most compute-intensive algorithm)
- **Graph size**: 22,036 vertices
- **Top PageRank score**: 6.246 (3 videos tied)
- **Convergence**: Successfully completed all iterations

Network Statistics (Degree Distribution)

- From all_degrees.describe():
- **Average in-degree**: 2.27 (mean connections per video)
- **Average out-degree**: 2.27
- **Std deviation (in)**: 3.42
- **Std deviation (out)**: 6.33 (suggests some highly connected hub videos)
- **Max in-degree**: 46 (most referenced video)
- **Max out-degree**: 20 (video with most outgoing links)
- **Min degree**: 0 (isolated videos)

Overall Performance Summary

Metric	Value
Total execution time	~90-100 seconds
Total videos in dataset	~860,000+
Total video snapshots	Unknown (not counted)
Total edges processed	50,000 (sampled)
Graph vertices	22,036
Memory usage	4GB driver, 4GB executor
Shuffle partitions	8
Most expensive operation	PageRank (~70% of total time)

Accuracy Metrics

- **Data completeness**: 100% for sampled subset
- **PageRank convergence**: Achieved after 10 iterations
- **Degree distribution**: Realistic power-law distribution (high std deviation)
- **Data quality issues**: Case sensitivity in category filtering (2 queries returned 0 results)

Scalability Observations

- **Current scale**: 50K edges, 22K vertices
- **Designed for scale**: Configurable sample size, partitioning strategy
- **Bottleneck**: Graph algorithms (PageRank) are memory-intensive
- **Optimization**: Repartitioning (10 partitions) reduces shuffle overhead

c. Describe how you plan to present the results to the user. Perhaps you plan to run the algorithm on demand and present the results to the user, or you plan to execute the algorithms offline, store their results, and present the results on demand.

We will do offline execution and store the result (NOT on demand).

Every time we insert a new crawl into the database, we can rerun our algorithms so that the analytics are up-to-date. Our GUI will access the current state of the analytics algorithm results, and we don't have to worry about dynamically updating.

If we do want to include dynamic algorithm processing, we can do that in the future. For now we will focus on static GUI, as it is more attainable within the project schedule.

4. Algorithm Scalability:

d. Have you implemented the algorithm with scalability in mind? If so, describe how lll your algorithm will scale in a distributed storage and processing environment.

Algorithm 1: Degree Distribution Computation

- Operations use embarrassingly parallel primitives:

    - GROUP BY on src/dst
    - single-key outer join
    - aggregations
- Each partition computes local degree counts independently, then merges results. No sequential bottlenecks.
- Scales linearly: O(E/P) where E = edges, P = partitions.

Algorithm 2: Categorized Video Statistics

- Category grouping and bucketing transformations are pure map operations with no cross-partition dependencies.
- Each video processes independently.
- Multiple aggregations execute as parallel query plans.
- Scales linearly with cluster size.

Algorithm 3: Top-K Queries

- Category counting and range filtering use distributed GROUP BY with predicate pushdown.
- Spark's external merge sort handles large-scale ordering.
- All queries are independent and fully parallelizable.

Algorithm 4: Subgraph Pattern Search (Motifs)

- GraphFrames' find() distributes pattern matching via edge partitioning.
- Simple 2-vertex patterns (a)-[e]->(b) scale well with O(E) complexity.
- Each executor searches local edge subset independently.

Algorithm 5: Influence Analysis Using PageRank

- GraphFrames' pageRank() method distributes computation across graph partitions (10 iterations, reset probability 0.15).
- Window function for latest snapshots partitions by video_id (fully parallel).
- Join between PageRank vertices and snapshots uses hash partitioning on video ID.

5. Source Code:
    - Provide the source code of your algorithms in a ZIP file.

Submitted with the assignment.