# Big Data Analysis on Million Song Dataset (MSD) ECE4721J: Methods and Tools for Big Data

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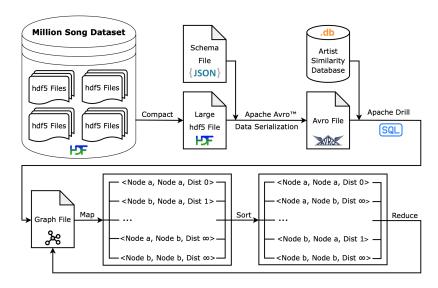




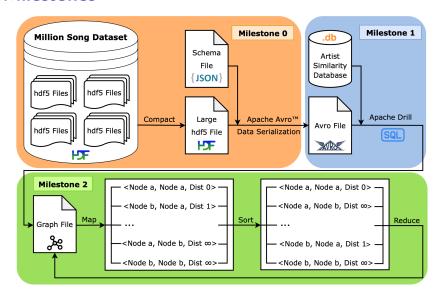
#### **Overview**

- Milestone 0: HDF5 Data Pre-process
- Milestone 1: Drill Database Query
- Milestone 2: Advanced Data Analysis

#### Workflow



#### **Milestones**



## Section 1

Milestone 0: HDF5 Data Pre-process

#### **Goals**

- 1. Compact small hdf5 files into larger one
- 2. Read hdf5 file and extract the information
- 3. Convert hdf5 to Avro with Apache Avro

## 1. Compact small hdf5 files into larger one

- \$ python3 create\_aggregate\_file.py <IN> <OUT>
  - Input: a directory contains hdf5 song files
  - Output: an aggregate hdf5 song file
  - Example:

Figure 1: Compact 10000 hdf5 files into larger one

## 2. Read hdf5 files and extract the information

- \$ python3 display\_song.py [FLAGS] <HDF5> <idx> <field>
  - Input: an hdf5 song file
  - Output: specified field content
  - Example:

Figure 2: Get artist name of the second song in compacted hdf5 file

# 3. Convert hdf5 to Avro with Apache Avro

- \$ hdf5\_to\_avro.py [-h] -s <SCHEMA> -i <HDF5> -o <AVRO>
  - Input:
    - an Avro schema file
    - an hdf5 song file to be converted
  - Output: an Avro song file

# Sample schema file in json format:

```
"namespace": "song.avro",
"type": "record",
"name": "Song",
"fields": [
    "name": "artist_name",
    "type": ["string", "null"]
 },
    "name": "title",
    "type": ["string", "null"]
```

```
root@hadoop-master:/home/s/pi1/m0# python3 src/hdf5 to avro.py -s schema/songs
.avsc -i data/compact.h5 -o data/output.avro
21:18:10 [Info] Convert a song file from hdf5 to Avro...
21:18:10 [Info] Avro schema path: schema/songs.avsc
21:18:10 [Info] hdf5 input path: data/compact.h5
21:18:10 [Info] Avro output path: data/output.avro
21:18:10 [Info] Avro schema file and hdf5 file exist
21:18:10 [Warning] Avro output file data/output.avro already exists
21:18:10 [Info] Parsing the Avro schema file...
21:18:10 [Info] Get the following fields:
               artist hotttnesss ["float", "null"]
              artist id ["string", "null"]
              artist_name ["string", "null"]
                             ["float", "null"]
              energy ["float", "null"]
               release ["string", "null"]
               song hotttnesss ["float", "null"]
              song_id
                                 "string"
                              ["float", "null"]
               title ["string", "null"]
               track_id ["string", "null"]
                                 ["int", "null"]
21:18:10 [Info] Found 10000 song(s)
21:18:10 [Info] Start converting hdf5 to Avro
21:18:10 Converting: 100%|
                                | 10000/10000 [00:22<00:00, 436.24it/s]
```

Figure 3: Convert compacted hdf5 file to Avro

## Section 2

Milestone 1: Drill Database Query

## **Goals**

Query Million Song Dataset (MSD) with Drill:

- 1. Find the range of dates covered by the songs in the dataset
- 2. Find the hottest song that is the shortest and shows highest energy with lowest tempo
- 3. Find the name of the album with the most tracks
- 4. Find the name of the band who recorded the longest song

# 1. The range of dates covered by the songs

SQL:

```
-- Age of the oldest songs

SELECT 2022 - MAX(year) AS Age

FROM hdfs.`/pj/m0/output.avro`;

-- Age of the youngest songs

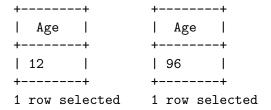
SELECT 2022 - MIN(year) AS Age

FROM hdfs.`/pj/m0/output.avro`

WHERE year > 0;
```

# 1. The range of dates covered by the songs

Results:



The oldest song's age is **96** and the youngest is **12**. As a result, the range of dates covered by the songs is **84** years.

# 2. The hottest song that is the shortest and shows highest energy with lowest tempo

SQL:

```
SELECT title
FROM hdfs.`/pj/m0/output.avro`
WHERE song_hotttnesss <> 'NaN'
ORDER BY song_hotttnesss DESC,
duration ASC,
energy DESC,
tempo ASC
LIMIT 10;
```

 Remarks: This query returns 5648 results, but we only display the first 10 records.

# 2. The hottest song that is the shortest and shows highest energy with lowest tempo

```
title
 b'Immigrant Song (Album Version)'
 b"Nothin' On You [feat. Bruno Mars] (Album Version)"
 b'This Christmas (LP Version)'
 b'If Today Was Your Last Day (Album Version)'
 b'Harder To Breathe'
 b'Blue Orchid'
| b'Just Say Yes'
 b'They Reminisce Over You (Single Version)'
 b'Exogenesis: Symphony Part 1 [Overture]'
 b'Inertiatic Esp'
10 rows selected (0.471 seconds)
```

## 3. The name of the album with the most tracks

• SQL:

```
SELECT release, COUNT(release) AS NumTrack
FROM hdfs.`/pj/m0/output.avro`
GROUP BY release
ORDER BY NumTrack desc
LIMIT 1;
```

Results:

```
+-----+
| release | NumTrack |
+-----+
| b'Greatest Hits' | 21 |
+-----+
1 row selected (0.695 seconds)
```

# 4. The name of the band who recorded the longest song

• SQL:

```
SELECT artist_name, duration
FROM hdfs.`/pj/m0/output.avro`
ORDER BY duration DESC
LIMIT 1;
```

Results:

```
+-----+
| artist_name | duration |
+-----+
| b'UFO' | 1819.7677 |
+-----+
1 row selected (0.27 seconds)
```

## Section 3

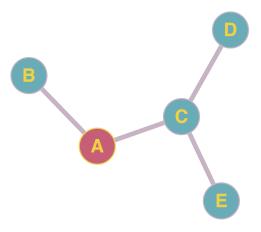
Milestone 2: Advanced Data Analysis

#### **Goals**

- Determine distance between artists with adjacency matrix, using parallelized BFS
- 2. Propose similar songs with distance and "provide more diverse recommendations"
- 3. Implement the above algorithm in both Mapreduce and Spark
- 4. Compare the performance of Mapreduce and Spark

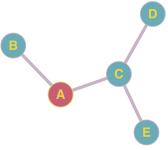
# BFS with MapReduce - A Simple Example

Let's say we want to find artists similar to  $\bf A$  with distance  $\bf 3$ , and we have following relationships (each edge has distance  $\bf 1$ ):



## Step 1: Initialize Graph File with Target Artist

Format: each line contains Node | Distance | Neighbours



A | O | A,B,C B | \omega | A,B C | \omega | A,C,D,E D | \omega | C,D E | \omega | C,E

Figure 5: Initialize Graph File

## Step 2: Generate Distance Pairs in Mapper

Mapper: Generate Neighbours, Node, Distance+1 if not itself

A|O|A,B,C  $B \mid \omega \mid A, B$  $C \mid \omega \mid A, C, D, E$  $D \mid \omega \mid C, D$  $E | \omega | C, E$ 

Мар

A, A, O B, A, 1 C, A, 1 Α, Β, ω Β, Β, ω Α, C, ω C, C, w D, C, ω E, C, ω C, D,  $\omega$ D, D, ω C, Ε, ω Ε, Ε, ω

A, A, O Α, Β, ω Α, C, ω B, A, 1 Β, Β, ω C, A, 1 C, C, w C, D, w C, Ε, ω D, C, w D, D, ω Ε, C, ω Ε, Ε, ω

# Step 3: Merge Distance Pairs in Reducer

Reducer: Merge the same Neighbour, keep distance minimum

Β, Β, ω C, D, w C, E,  $\omega$ D, C, ω

 $A \mid O \mid A, B, C$ B|1|A,BC|1|A,C,D,EReduce  $D \mid \omega \mid C, D$  $E \mid \omega \mid C, E$ 

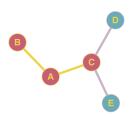


Figure 6: Graph after 1 MapReduce Iteration

## **Iteraiton 2: Mapper**

A|O|A,B,C

B|1|A,B

C|1|A,C,D,E

 $D \mid \omega \mid C, D$ 

 $E | \omega | C, E$ 

Мар

C, A, 1
A, B, 2
B, B, 1
A, C, 2
C, C, 1
D, C, 2
E, C, 2
C, D, \omega
D, D, \omega

C, E, 0

Ε, Ε, ω

A, A, O

B, A, 1

Sort

A, A, O A, C, 2 A, B, 2 B, A, 1 B, B, 1 C, A, 1 C, C, 1 C, D, w C, E, 0 D, C, 2  $D, D, \omega$ E, C, 2 Ε, Ε, ω

## **Iteration 2: Reducer**

A, A, O C, D, w C, E, 0 D, C, 2 D, D, ω

Reduce

A|O|A,B,C B|1|A,BC|1|A,C,D,ED|2|C,D E|2|C,E

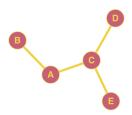


Figure 7: Graph after 2 MapReduce Iterations

# **BFS** with Spark

- Same algorithm as is proposed before
- Implemented using Python with PySpark
- For the implementation, we:
  - 1. Convert data into RDD map
  - 2. Using Spark sortByKey() to sort RDD aggregated by node index and then combining the neighbours
  - 3. Using Spark reduce() to pick the minimum distance of different neighbours towards the central node
- Spark is assumed to be faster since subsequent steps are retained in memory with a trade-off of much more memory consumption

#### **Benchmark**

- Data size: around 200GB
- Server: SJTU cluster with three machines
  - CPU: Dualcore Intel Xeon Processor (Skylake, IBRS)
  - Memory: 4GB

```
Searching for ARRMHA01187B9B9455
Time for MapReduce is 252 s
Searching for ARLGLTR1271F574286
Time for MapReduce is 250 s
Searching for ARRXPRY1187B9A8B34
Time for MapReduce is 252 s
Searching for AR1WWVL1187B9B0306
Time for MapReduce is 252 s
Searching for ARSRZFI11E2835D13C
Time for MapReduce is 252 s
```

```
(*ARZZQQ12599411C96*, (*ARSGH21187F84683E*, ARCLH9U1

*ARGYMS1187F846884*, 'ARGXNL91187F843641*, ARH1PM91

*ARHIETG1187F841238*, 'ARNXAVA1187F843670*, 'ARH1PM91

*ARHIETG1187F841238*, 'ARXXAVA1187F846570*, 'ARPARS591

*ARVECE11878983008*, 'ARZZQ212594411C96**,' 1, 10000,

*ARVECE11878983008*, 'ARVECE118318C5844*, 'ARGGLES1

*ARVECE11878983008*, 'ARVECE118318C5844*, 'ARGGLES1

*ARVECE11878983008*, 'ARVECE118318C5844*, 'ARGGLES1

*ARCEMUNT.1950.445488*, (*C.*ARXVB1187889801A*, 'ARGGLES1

*ARCEMUNT.1950.445488*, (*C.*ARXVB1187880586*, 'ARGGLES1

*ARCEMUNT.1950.445488*, 'C.*ARXVB1187880587*, 'ARVECE11878989349C*, 'ARVECE11875046486*, 'ARGGLES1

*ARTCAT51187893949C*, 'ARVECE1187504686*, 'ARVECE118750468881*, 'ARVECE1187504686*, 'ARVECE118750468881*, 'ARVECE118759890666*, 'C.*ARCATACT*, '10000,

*C.*ARZZYRB11878990066*, (*C.*ARZXB11871850468881*, 'ARZZYRB11878950066*, 'ARZZYRG11878950866*, 'C.*ARZZYRB11878950066*, 'C.*ARZZYRB11878950066*, 'C.*ARZZYRB11878950066*, 'C.*ARZZYRB11878950066*, 'C.*ARZZYRB11878950066*, 'C.*ARZZYRB11878950066*, 'C.*ARZZYRB11878950066*, 'C.*ARZZYRB11878950066*, 'ARZZYRB11878950066*, 'ARZZYRB11878950066*, 'ARZZYRB11878950066*, 'C.*ARZZYRB11878950066*, 'ARZZYRB11878950066*, 'C.*ARZZYRB11878950066*, 'ARZZYRB11878950066*, 'ARZZYRB11878950066*, 'ARZZYRB1187895006*, 'ARZZYRB11878950066*, 'ARZZYRB11878950066*,
```

Figure 8: MapReduce: around 250s

Figure 9: Spark: around 45s

#### Reference

Million Song Dataset
 http://millionsongdataset.com

2. Apache Avro Documentation
 https://avro.apache.org/docs/current/index.html

Apache Spark Documentation https://spark.apache.org/docs/latest/

## Thanks for your attention!



Figure 10: Never Gonna Give You Up (by Rick Astley)