Programming for Big Data

Project Report: YouTube Video Analysis

Group Members

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Project Idea:

Introduction:

YouTube is one of the most popular web sites on the internet today. The reason being millions of creators coming together to share their content. This content ranges from high budget and amazing movie trailers to silly cat videos. Majority of the YouTube videos are free to the public to view. Also, anyone can upload their own video being an individual or an organization. As a result, the dataset of YouTube is massive and immensely interesting for analysts like us.

Motivation:

YouTube contains a section called as the 'Trending videos'. In this section, the videos which are currently popular and liked by majority of the YouTubers are displayed. This section contains videos from all the categories; be it music or documentaries. However, it may be of little use to the user who wants to search for the videos of his liking. What if the user wants to search the trending videos of 'photography'? Unfortunately, YouTube doesn't provide any such functionality. This seemed like an interesting and challenging problem to be solved. Hence, in this project, we have made an effort to provide this functionality of displaying the trending videos of different categories.

Problem Statement:

1. We can see the categories in Trending section in YouTube. But the way it works is that YouTube categorizes the videos which are in the Trending section. But it doesn't provide the trending videos for each category, i.e., you can see the categories of the videos which are currently trending, but you cannot see the trending videos of different categories. Our project works on providing the latter.
2. We are also doing analysis on hot tags of trending videos which uploaders can use while describing their videos to receive more hits.
3. We have also tried to create a model to predict if the new obtained video will feature in our Categorically Trending Videos or not.

Dataset:

We have used the YouTube Developer API to fetch the video dataset and also other important statistics related to those videos.

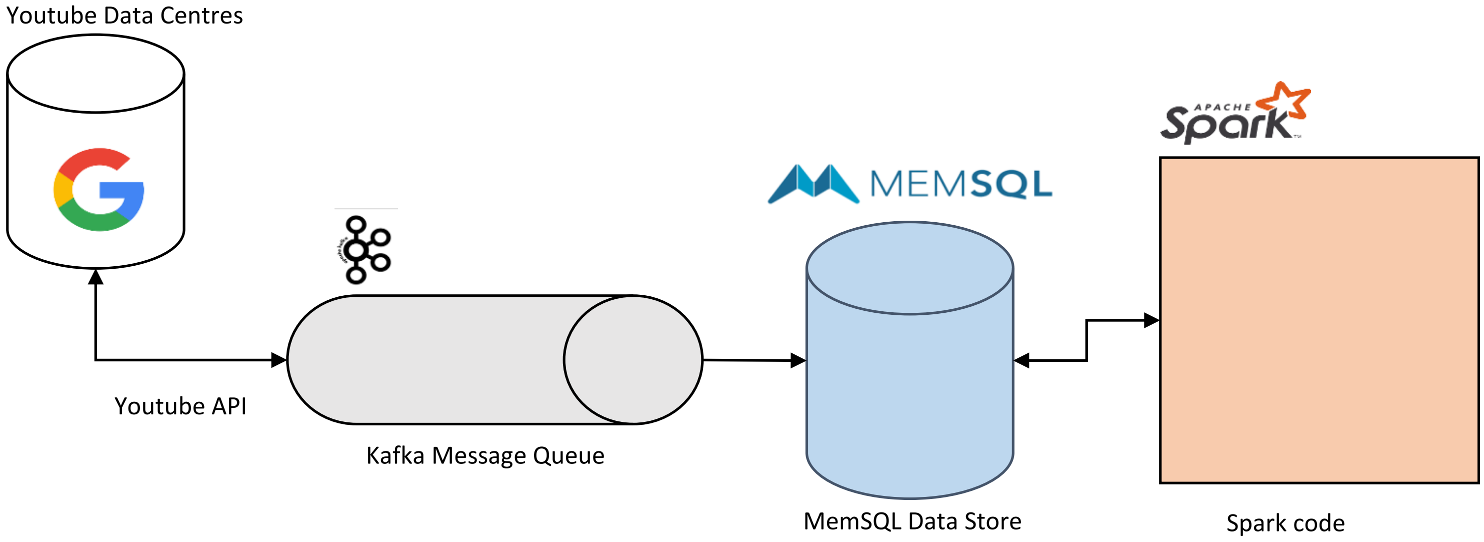
Link providing all the usage of the API is https://developers.google.com/youtube

Data includes the 'videoID', 'url', 'published time', 'channelID', 'category', 'viewCount', 'likeCount', 'dislikeCount' and so on.

Our dataset is about 100MB in size combined.

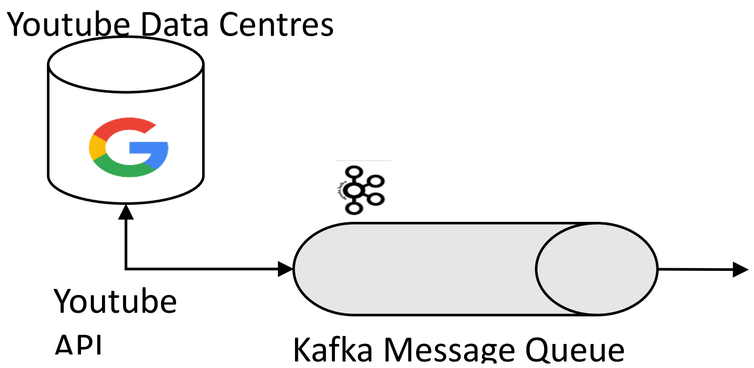
Technology:

Architecture Diagram



Component Break-Down

1. Kafka Message Queue:



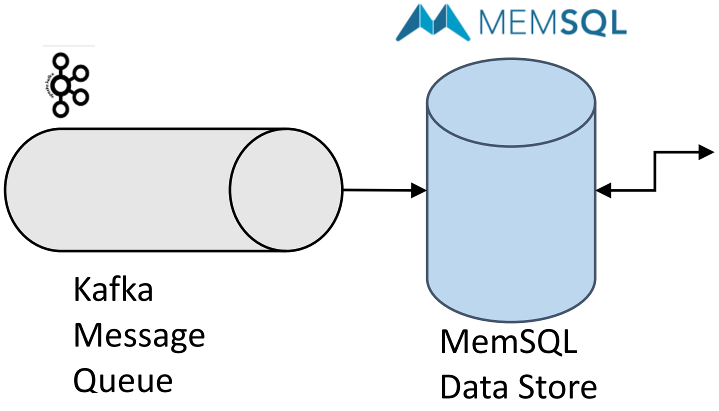
Description:

- Kafka Message Bus. It enables us to stream real-time data to our spark code to perform the analysis.
- There are two topics corresponding to 2 types of data which we receive from the API requests.
- The topics currently have 1 partition only. But, we can leverage this parameter to further partition the topics based on categories and so on. This will enable us to parallelize the analysis step further.
- Kafka follows a Producer/Consumer Model.
- We have created 2 topics in Kafka with 1 partition namely ‘videos_topic' and ‘statistics_topic’

Some code snippets:

```
//Producer Config
producer = KafkaProducer(bootstrap_servers= ['localhost:9092']
//Produce to ‘statistics_topic’
producer.send('statistics_topic', json.dumps(d))
//Produce to ‘videos_topic’
producer.send('videos_topic', json.dumps(data))
```

2. MemSQL:



Description:

- MemSQL is a real-time data warehouse for cloud and on-premises that delivers immediate insights across live and historical data.
- MemSQL is like an in-memory persistent Data Store which has two tables namely Video and Statistics which consume data from Kafka and maintain a persistent storage for the data.
- We have used this component since in our use case we could not perform analysis on live streaming data and required a batch or a set of data to be available.
- MemSQL pipelines consume data from Kafka and insert it into the Tables.

Creating Tables in MemSQL:

Table Video:

```
CREATE TABLE Video(
message JSON NOT NULL,
videoId AS message::$videoId PERSISTED varchar(20),
publishedAt AS message::$publishedAt PERSISTED varchar(20),
channelId AS message::$channelId PERSISTED varchar(100),
category AS message::$category PERSISTED varchar(20),
title AS message::$title PERSISTED VARCHAR(1000),
description AS message::$description PERSISTED varchar(5000),
url AS message::$url PERSISTED varchar(1000),
channelTitle AS message::$channelTitle PERSISTED varchar(100),
PRIMARY KEY(videoId),
SHARD KEY(videoId)
);
```

Table Statistics:

```
CREATE TABLE Statistics(
message JSON NOT NULL,
videoId AS message::$videoId PERSISTED varchar(20),
viewCount AS message::$viewCount PERSISTED BIGINT,
likeCount AS message::$likeCount PERSISTED BIGINT,
dislikeCount AS message::$dislikeCount PERSISTED BIGINT,
favoriteCount AS message::$favoriteCount PERSISTED BIGINT,
commentCount AS message::$commentCount PERSISTED BIGINT,
PRIMARY KEY(videoId),
SHARD KEY(videoId)
);
```

Creating Pipelines to Connect to Kafka Topics:

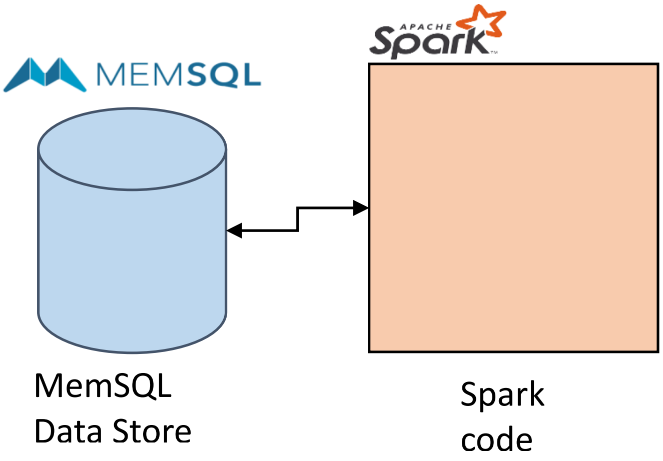
Pipeline for Video Table:

```
CREATE PIPELINE IF NOT EXISTS TEST_Video
AS LOAD DATA KAFKA 'localhost:9092/videos_topic'
BATCH_INTERVAL 2500
SKIP ALL ERRORS
REPLACE
INTO TABLE Video
FIELDS TERMINATED BY '\t' ENCLOSED BY '' ESCAPED BY ''
LINES TERMINATED BY '\n' STARTING BY ''
(`message`);
```

Pipeline for Statistics Table:

```
CREATE PIPELINE IF NOT EXISTS TEST_Statistics
AS LOAD DATA KAFKA 'localhost:9092/statistics_topic'
BATCH_INTERVAL 2500
SKIP ALL ERRORS
REPLACE
INTO TABLE Statistics
FIELDS TERMINATED BY '\t' ENCLOSED BY '' ESCAPED BY ''
LINES TERMINATED BY '\n' STARTING BY ''
(`message`);
```

3. Spark



Description:

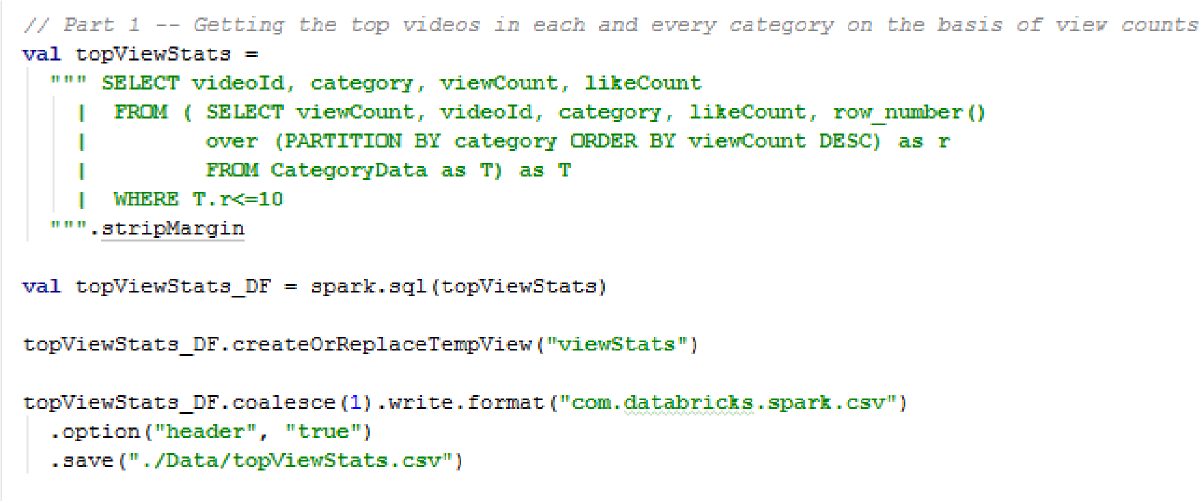
- Spark as we know, one the best technologies to work with Big Data. Even though currently we do not have such huge amount of data, but with YouTube Data we can be safe to assume that we will have to deal with Big Data in practical purposes.
- We have leveraged the Spark SQL abilities to perform various types of analysis on the data we received out of YouTube.
- Spark constantly queries the MemSQL tables to fetch data and perform analysis.
- We can also write out results back into some result table in MemSQL.
- We have used scala to write spark code.

Work Accomplished

Analysis:

1. To find the top trending videos in each category.

Code snippet (based on View Count):



```
// Part 1 -- Getting the top videos in each and every category on the basis of view counts
val topViewStats =
  """ SELECT videoId, category, viewCount, likeCount
    |  FROM ( SELECT viewCount, videoId, category, likeCount, row_number()
    |         over (PARTITION BY category ORDER BY viewCount DESC) as r
    |         FROM CategoryData as T) as T
    |  WHERE T.r<=10
  """.stripMargin

val topViewStats_DF = spark.sql(topViewStats)

topViewStats_DF.createOrReplaceTempView("viewStats")

topViewStats_DF.coalesce(1).write.format("com.databricks.spark.csv")
  .option("header", "true")
  .save("./Data/topViewStats.csv")
```

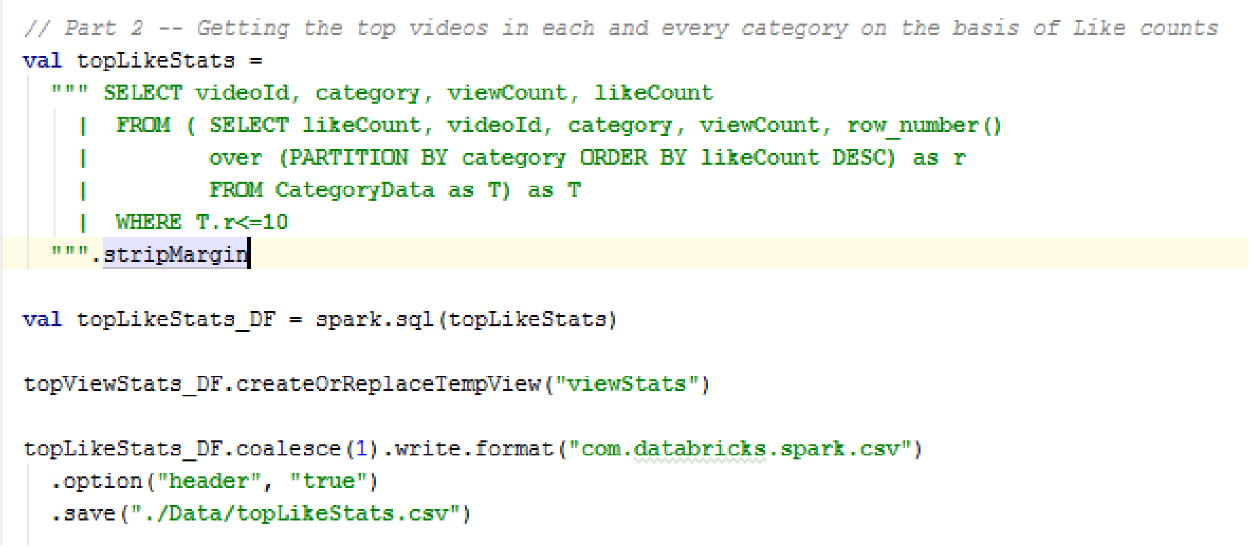
Here we get top 10 videos in each category based on View_Count

Output:

Output file : “Data/topViewStats.csv”

<vis image>>

Code snippet (based on Like Count):



```
// Part 2 -- Getting the top videos in each and every category on the basis of Like counts
val topLikeStats =
  """ SELECT videoId, category, viewCount, likeCount
    |  FROM ( SELECT likeCount, videoId, category, viewCount, row_number()
    |         over (PARTITION BY category ORDER BY likeCount DESC) as r
    |         FROM CategoryData as T) as T
    |  WHERE T.r<=10
  """.stripMargin

val topLikeStats_DF = spark.sql(topLikeStats)

topViewStats_DF.createOrReplaceTempView("viewStats")

topLikeStats_DF.coalesce(1).write.format("com.databricks.spark.csv")
  .option("header", "true")
  .save("./Data/topLikeStats.csv")
```

Here we get top 10 videos in each category based on Like_Count

Output:

Output file : “Data/topLikeStats.csv”

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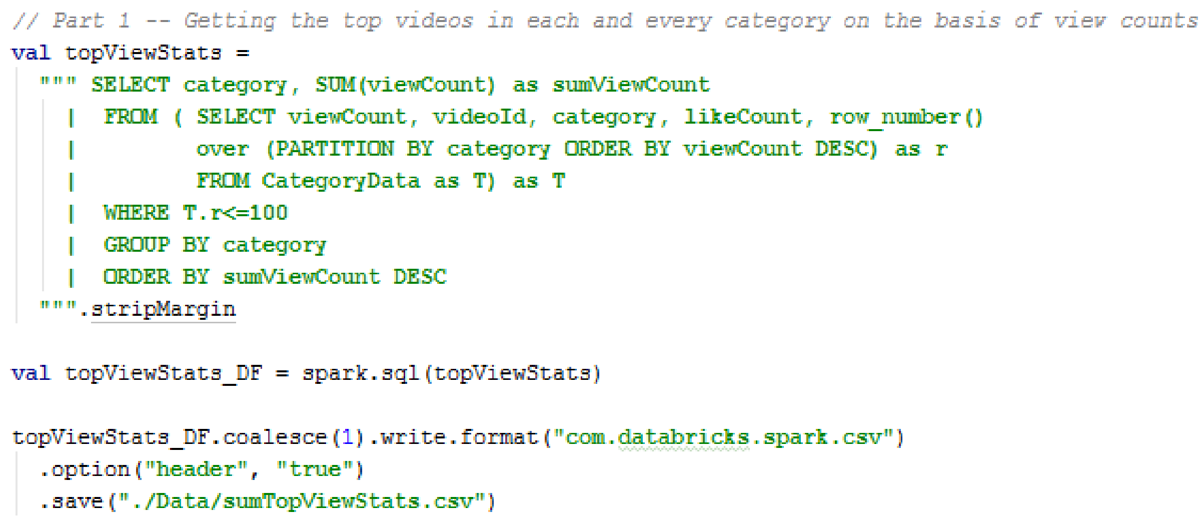
2. To find the trending category based on views of videos.

Code snippet:



```
// Part 1 -- Getting the top videos in each and every category on the basis of view counts
val topViewStats =
  """ SELECT category, SUM(viewCount) as sumViewCount
    |  FROM ( SELECT viewCount, videoId, category, likeCount, row_number()
    |         over (PARTITION BY category ORDER BY viewCount DESC) as r
    |         FROM CategoryData as T) as T
    |  WHERE T.r<=100
    |  GROUP BY category
    |  ORDER BY sumViewCount DESC
  """.stripMargin

val topViewStats_DF = spark.sql(topViewStats)

topViewStats_DF.coalesce(1).write.format("com.databricks.spark.csv")
  .option("header", "true")
  .save("./Data/sumTopViewStats.csv")
```

Here we get top category based on the sum of ViewCount of top 100 videos in each category.

Output:

Output file : “Data/sumTopViewStats.csv”

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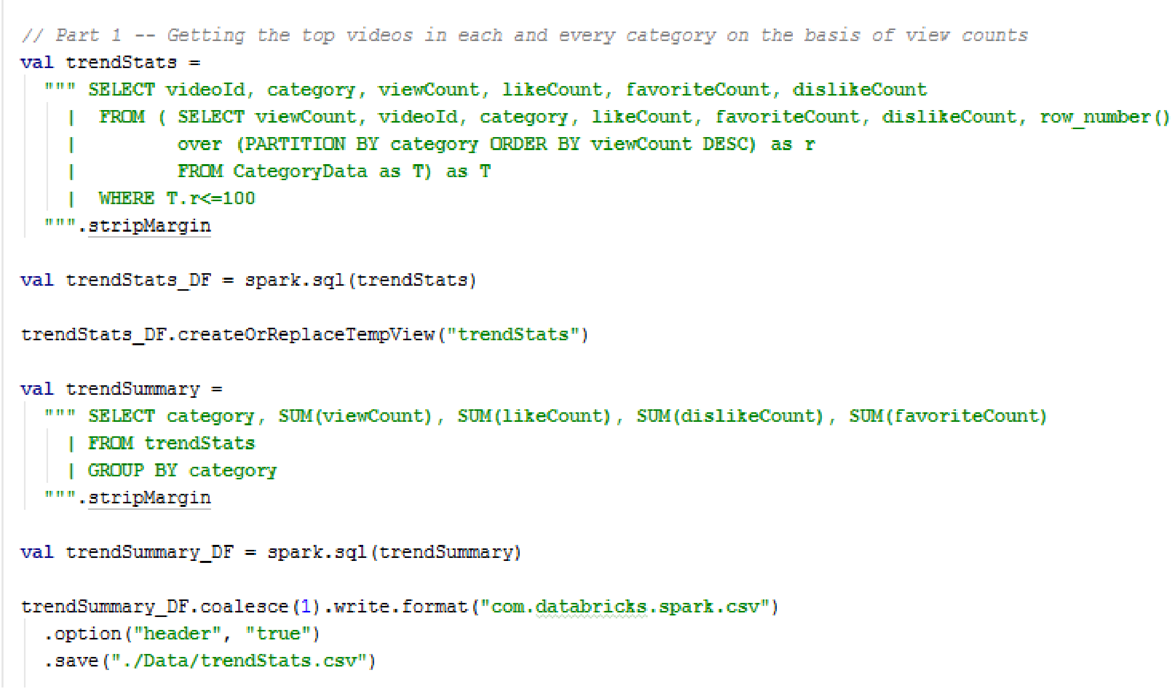
3. Analysis of categories.

Code snippet:



```
// Part 1 -- Getting the top videos in each and every category on the basis of view counts
val trendStats =
  """ SELECT videoId, category, viewCount, likeCount, favoriteCount, dislikeCount
    |  FROM ( SELECT viewCount, videoId, category, likeCount, favoriteCount, dislikeCount, row_number()
    |         over (PARTITION BY category ORDER BY viewCount DESC) as r
    |         FROM CategoryData as T) as T
    |  WHERE T.r<=100
  """.stripMargin

val trendStats_DF = spark.sql(trendStats)

trendStats_DF.createOrReplaceTempView("trendStats")

val trendSummary =
  """ SELECT category, SUM(viewCount), SUM(likeCount), SUM(dislikeCount), SUM(favoriteCount)
    | FROM trendStats
    | GROUP BY category
  """.stripMargin

val trendSummary_DF = spark.sql(trendSummary)

trendSummary_DF.coalesce(1).write.format("com.databricks.spark.csv")
  .option("header", "true")
  .save("./Data/trendStats.csv")
```

Here we analyze the statistics of each category based on the sum of ViewCount of top 100 videos in each category.

Output:

Output file : “Data/trendStats.csv”

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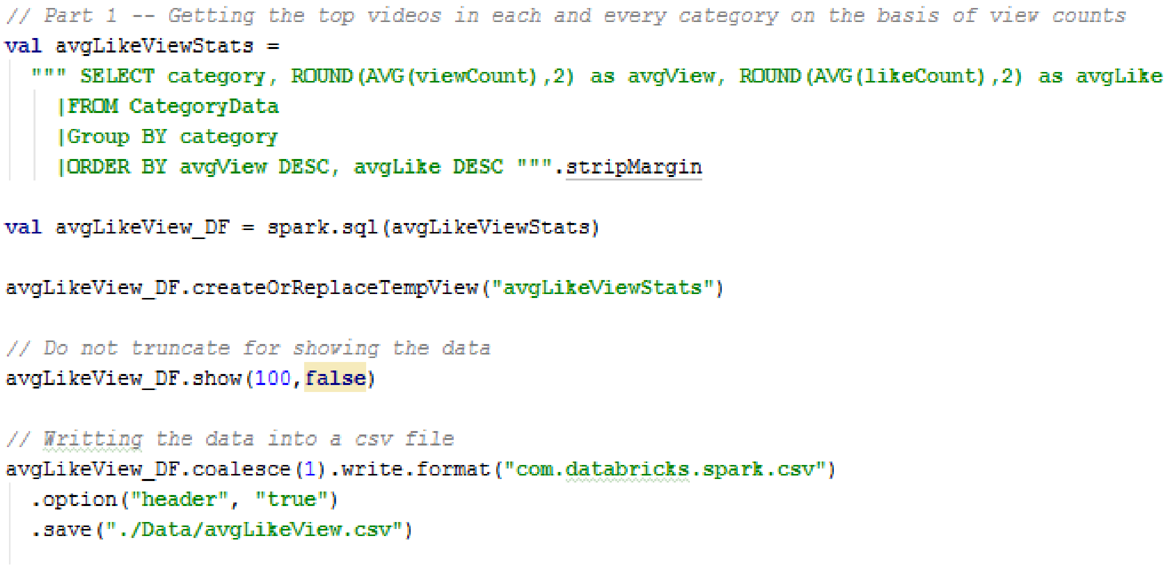
4. Average number of Views and average number of Likes for each category.

Code snippet:



```
// Part 1 -- Getting the top videos in each and every category on the basis of view counts
val avgLikeViewStats =
  """ SELECT category, ROUND(AVG(viewCount),2) as avgView, ROUND(AVG(likeCount),2) as avgLike
    |FROM CategoryData
    |Group BY category
    |ORDER BY avgView DESC, avgLike DESC """.stripMargin

val avgLikeView_DF = spark.sql(avgLikeViewStats)

avgLikeView_DF.createOrReplaceTempView("avgLikeViewStats")

// Do not truncate for showing the data
avgLikeView_DF.show(100,false)

// Writting the data into a csv file
avgLikeView_DF.coalesce(1).write.format("com.databricks.spark.csv")
  .option("header", "true")
  .save("./Data/avgLikeView.csv")
```

Here we get the avg of Views and Likes of each category.

Output:

Output file : “Data/avgLikeView.csv”

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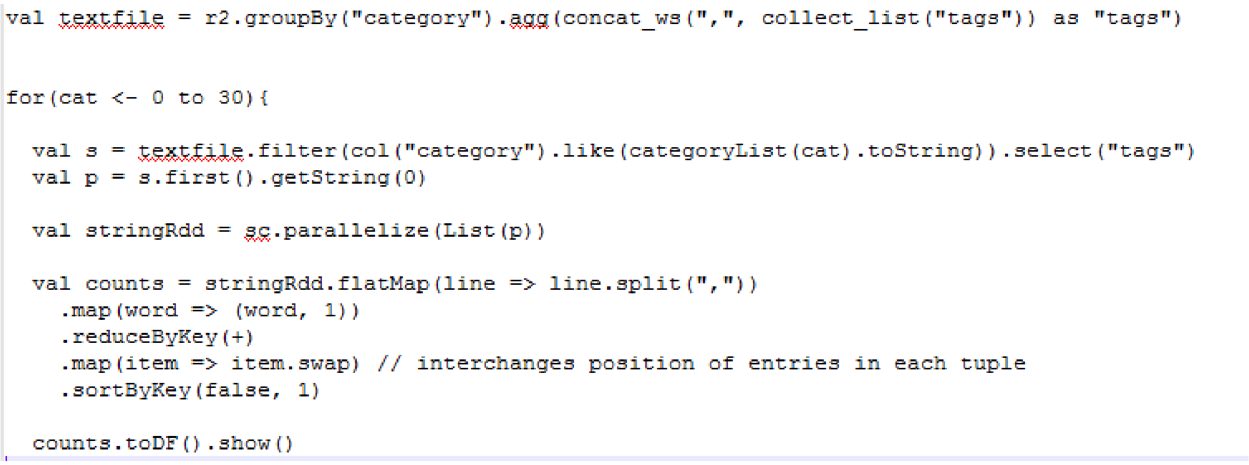
5. Identifying Hot Tags for each Category.

Code snippet:



```
val textfile = r2.groupBy("category").agg(concat_ws(",", collect_list("tags")) as "tags")


for(cat <- 0 to 30){

  val s = textfile.filter(col("category").like(categoryList(cat).toString)).select("tags")
  val p = s.first().getString(0)

  val stringRdd = sc.parallelize(List(p))

  val counts = stringRdd.flatMap(line => line.split(","))
    .map(word => (word, 1))
    .reduceByKey(+)
    .map(item => item.swap) // interchanges position of entries in each tuple
    .sortByKey(false, 1)

  counts.toDF().show()
```

Here we have preformed word count using map-reduce for each category. This gives us the list of hot tags in each category which the uploader could use in his video description helping him get more hits.

This was executed on NYU HPC to leverage the high computing power required to perform this task.

Output:

Output file : “Data/avgLikeView.csv”

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6. Predicting if the new obtained video can feature in the trending video list.