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CS 644 004 Introduction to Big Data

Project: Flight Data Analysis

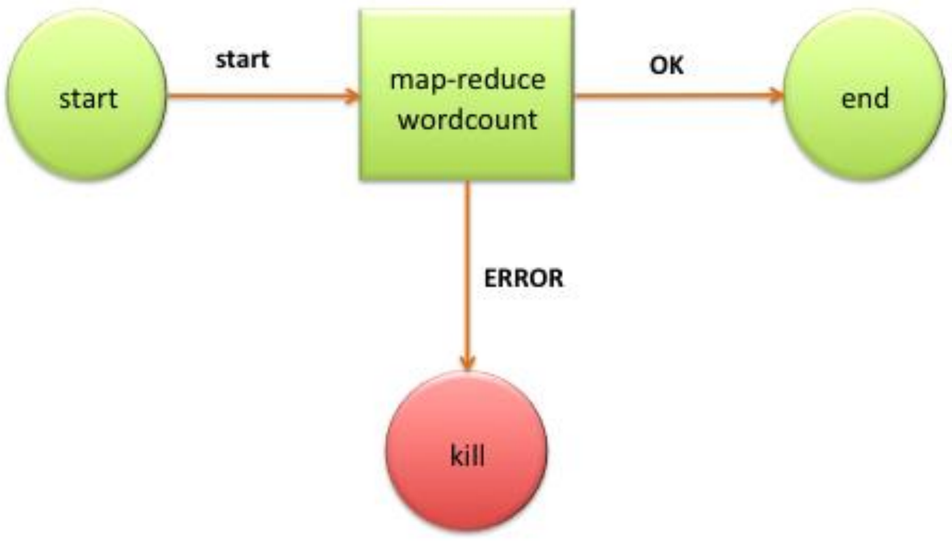
Introduction:

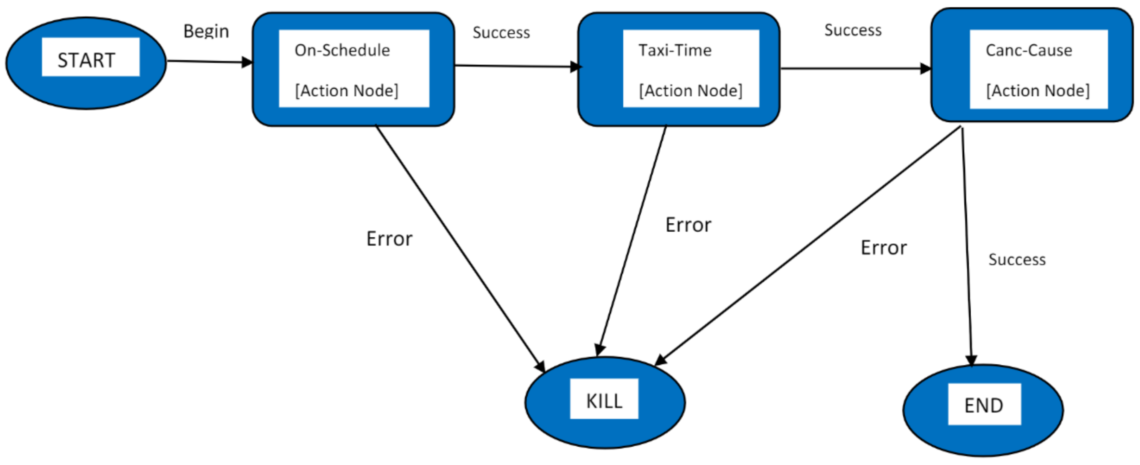
In this project, we analyze the Airline On-time Performance dataset spanning from October 1987 to April 2008. The objective is to use big data tools on AWS virtual machines (VMs), in Oozie, to find insights into the operational efficiency of airports and airlines and cancellations of flights.

Data Set: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/HG7NV7

Milestone: 1

- **Workflow in Oozie Hadoop**





1.Finding Top 3 Airlines with the Highest and Lowest Probability of Being on Schedule:

Objective: Calculate the probability that each airline's flights are on time.

MapReduce Job 1:

Mapper: Each mapper reads a flight record and extracts information about the airline and whether the flight was on time or delayed.
Reducer: Receives the output from the mappers and calculates the probability of each airline being on schedule by dividing the number of on-time flights by the total number of flights for that airline.
Output: Provides key-value pairs where the key represents the airline code and the value represents the calculated probability of being on schedule.
MapReduce Job 2:

Mapper: Identifies the top 3 airlines with the highest probability of being on schedule by sorting the key-value pairs from Job 1.
Reducer: Selects the top 3 airlines with the highest probabilities based on the sorted data.
Output: Presents key-value pairs of the top 3 airlines with the highest probability of being on schedule.

MapReduce Job 3:

Mapper: Identifies the top 3 airlines with the lowest probability of being on schedule by sorting the key-value pairs from Job 1.
Reducer: Selects the top 3 airlines with the lowest probabilities based on the sorted data.
Output: Provides key-value pairs of the top 3 airlines with the lowest probability of being on schedule.

2. Finding Top 3 Airports with the Longest and Shortest Average Taxi Time per Flight:

Objective: Determine the average taxi-in and taxi-out times for each airport.

MapReduce Job 4:

Mapper: Extracts airport and taxi time data from input records.
Reducer: Calculates the average taxi time for each airport for both inbound and outbound flights.
Output: Yields key-value pairs where the key represents the airport code and the value represents the average taxi time.

MapReduce Job 5:

Mapper: Identifies the top 3 airports with the longest average taxi time by sorting the key-value pairs from Job 4.
Reducer: Selects the top 3 airports with the longest average taxi time based on the sorted data.
Output: Presents key-value pairs of the top 3 airports with the longest average taxi time.

MapReduce Job 6:

Mapper: Identifies the top 3 airports with the shortest average taxi time by sorting the key-value pairs from Job 4.
Reducer: Selects the top 3 airports with the shortest average taxi time based on the sorted data.
Output: Provides key-value pairs of the top 3 airports with the shortest average taxi time.

3.Finding the Most Common Reason for Flight Cancellations:

Objective: Identify the most common reasons for flight cancellations.

MapReduce Job 7:

Mapper: Extracts cancellation reason data from input records.
Reducer: Counts the occurrences of each cancellation reason.
Output: Produces key-value pairs where the key represents the cancellation reason and the value represents the count.

MapReduce Job 8:

Mapper: Identifies the cancellation reason with the highest count.
Reducer: Selects the cancellation reason with the highest count.
Output: Provides a key-value pair of the most common cancellation reason.

Milestone: 2

1. Find the 3 airlines with the highest and lowest probability, respectively, for being on schedule

(1) MapperOne

Since each airline and flight number combination is unique, we can combine them as keys here. MapperOne calculates the sum of ArrDelay and DepDelay for each flight (each row in the table).
If this time is longer than the starting time (15 minutes), it can be considered that the flight did not take off as planned. This is followed by total content (total 1) and total content (count 1). In addition, all airline flights will be postponed and all flights will increase by one. Otherwise, when the sum of ArrDelay and DepDelay is not more than the threshold value, it means that the flight is on time, in this case we need to add 1 to the flight time from the written points (count 1). This will not change the aircraft's flight delay; it will only increase the total flight time by 1.

(2) ReducerOne

To calculate the on_schedule result, you need all flights of each airline and all flights of that airline that are not on_schedule. Then, each carrier's total flights are included, as well as the number of non-scheduled flights. So here, divide the two numbers, the number of unscheduled flights and the total number of flights, to find the delay of each plane. In this reducer the delay will be stored in a link. Then, by analyzing these ongoing links, we can buy the plane with the best performance at that moment by analyzing the links below, we voluntarily buy the plane in the least amount of time. Keep two lists of size 3 to determine the highest percentage of on-time flights and the lowest percentage of on-time flights.

2. Find the 3 airports with the longest and shortest average taxi time per flight (both in and out), respectively

(1) Mapper Two

Mapper Two use airport code as key and corresponding taxi time as value. It produces the Origin airport and departure taxi time (Origin, taxiTime) and taxi out time (Dest, taxiTime).

(2) Reducer Two

ReducerTwo calculates the total taxi time (arrival time and departure time) for each airport by summing the TaxIn and TaxiOut values. ReducerTwo also calculates all flights for each airport. The total taxi time is divided by the number of flights and the average taxi time can be calculated from these two values. This value will then be saved in a file attachment. Then, by checking the decision to go up through this list, we can reach the airport as soon as possible by taxi ride. We can reach the airport as soon as possible by checking the name link. Keep two lists of size 3 to keep the airport with the highest average taxi season and the airport taxi season with the lowest.

3. Find the most common reason for flight cancellations

(1) MapperThree

MappercThree count this cancellation reason by context write the cancellation code and 1 when a flight is cancelled.

(2) ReducerThree

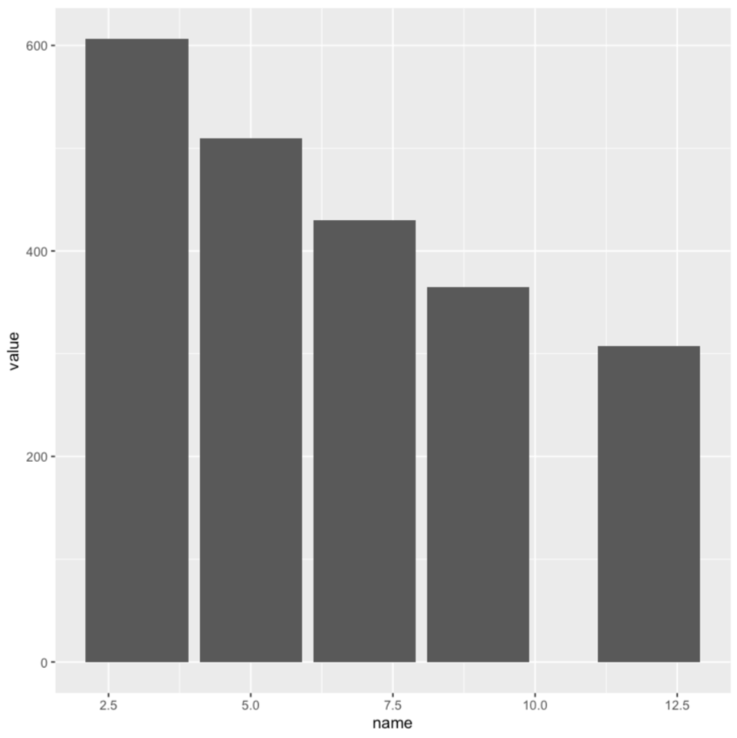
This Reducer is used to find the top cause of flight cancellation. All we need to do is manage the cancellation code with the most flight cancellations. The number of flights canceled for the same reason (same cancellation code) is counted here. When the number increases, it should be compared with the number of flights most frequently cancelled. If the calculated value is greater than the current maximum value, the cancel code is overridden and the calculated value is used as the new maximum value. This way you can find the most common reasons for flight cancellations.

4. Performance measurement

A performance measurement plot that compares the workflow execution time in response to an increasing number of VMs used for processing the entire data set (22 years)

Increase the cluster size from 3 to 12 nodes

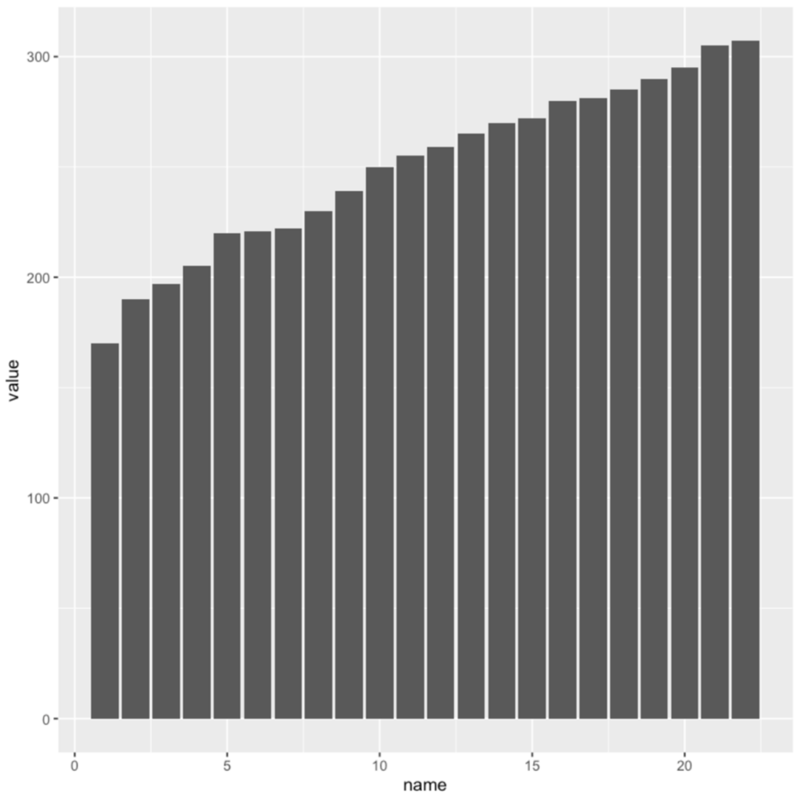
Cluster Size	**3**	**5**	**7**	**9**	**12**
Execution Time	10 min 6 s	8 min 30 s	7 min 10 s	6 min 5 s	5 min 7 s



- As the number of VMs increases from 3 to 12, there is a clear downward trend in the execution time.
- The most significant drop-in time occurs when moving from 3 VMs (10 min 6 s) to 5 VMs (8 min 30 s), suggesting that increasing the cluster size significantly boosts processing efficiency initially.
- The diminishing returns as VMs increase suggest a point of saturation were adding more VMs yields less benefit in terms of reducing execution time.
- A performance measurement plot that compares the workflow execution time in response to an increasing data size (from 1 year to 22 years)
- Changing dataset from 1 year to 22 years with 12 nodes

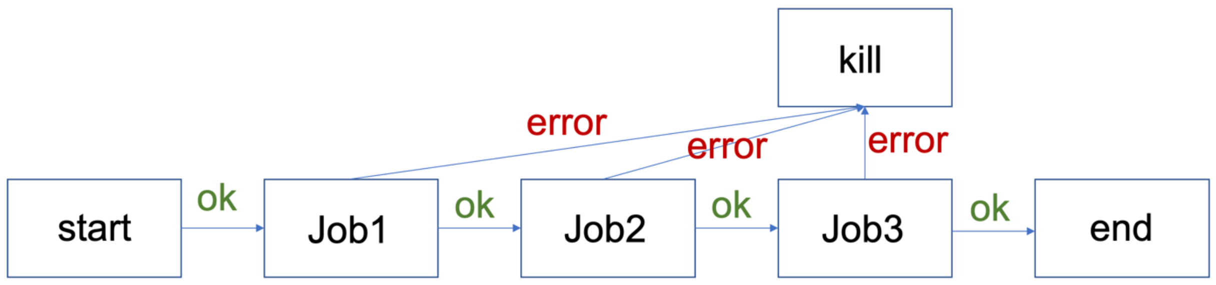
Years	**Time**
1	2 min 50 s
2	3 min 10 s
3	3 min 17 s
4	3 min 25 s
5	3 min 40 s
6	3 min 41 s
7	3 min 42 s
8	3 min 50 s
9	3 min 59 s
10	4 min 10 s
11	4 min 15 s
12	4 min 19 s
13	4 min 25 s
14	4 min 30 s
15	4 min 32 s
16	4 min 40 s

17	4 min 41 s
18	4 min 45 s
19	4 min 50 s
20	4 min 55 s
21	5 min 5 s
22	5 min 7 s



- Execution time increases almost linearly as the data size increases from 1 year to 22 years.
- The rate of increase in time is not uniform; slight variations occur, but overall, the trend shows a steady increment.
- The linear increase in execution time with data size indicates that the system scales proportionally, which is a desirable property in data processing systems.
- The slight fluctuations in the rate of increase might be influenced by factors such as data complexity or variations in data content for different years.
- Overall, the system appears to handle scaling in data size effectively, maintaining a manageable increase in execution time, which suggests good performance stability.

5. Workflow structure graph:


kill
error
error
error
start
ok
Job1
ok
Job2
ok
Job3
ok
end