Introduction

Driving is one of the most common yet dangerous tasks that people perform every day. According to the NHTSA, there is an average of 6 million accidents in the U.S. per year, resulting in over 2.35 million injuries and 37,000 deaths. [1] Additionally, road crashes cost the U.S. $230.6 billion per year. Various factors can contribute to accidents such as distracted driving, speeding, poor weather conditions, and alcohol involvement. However, using these factors and additional statistics, we can better predict the cause of accidents and put laws and procedures in place to help minimize the number of accidents. For this assignment, we used Apache Spark to analyze the motor vehicle collisions in New York City (NYC). Our goal was to use Spark to gain additional insights into the causes of accidents in the Big Apple, which can be used to help prevent certain accidents from occurring.

Datasets

The NYC Motor Vehicle Collisions - Crashes [2] dataset was the primary dataset used for our analysis. We also used NYC Motor Vehicle Crashes - Vehicle [3] and the 2015 NYC Tree Census [3] as our secondary datasets. All of the datasets were obtained from NYC OpenData in CSV format and contain the most up to date motor vehicle collision information available to the public.

NYC Motor Vehicle Collisions - Crashes:

This dataset contains information about the motor vehicle collisions in NYC from July 2012 to February 2020. The data was extracted from police reports (form MV104-AN) that were filed at the time of the crash. A form MV104-AN is only filed in the case where an individual is injured or fatally injured, or when the damage caused by the accident is $1,000 or greater. This dataset has 29 columns, 1.65 Million rows, and a size of 369 MB. Each row includes details about a specific motor vehicle collision.

NYC Motor Vehicle Crashes - Vehicle:

This dataset contains information about each vehicle that was involved in a crash in NYC from September 2012 to May 2020 and a police report MV104-AN was filed. This dataset has 3.35M rows, 25 columns, and a size of 566.3 MB. Each row represents the vehicle information for a specific crash, which can also be tied back to the NYC Motor Vehicle Collisions - Crashes dataset. Multiple vehicles can be involved in a single crash.

2015 NYC Tree Census: [4]

This dataset contains detailed information on the trees living throughout NYC collected by the NYC Parks and Recreation Board in 2015. This dataset has 684K rows, 45 columns, and has a size of 220.4 MB. Each row represents the information for a tree living in NYC.

Chosen Spark API for Answering Analytical Questions

I chose to use the Spark DataFrames API for my analysis. The Spark DataFrames API is similar to relational tables in SQL, however, it also provides a programmatic API allowing for more flexibility in query expressiveness, query testing, and is extensible. Additionally, the datasets that were chosen for our analysis are in a format that can be easily worked with using DataFrames. For example, our data is in a tabular format with columns and rows, which is how data is represented in DataFrames. Additionally, DataFrames inherits all of the properties of RDDs such as read-only, fault tolerance, caching, and lazy execution but with the additional data storage optimizations, code generation, query planner, and abstraction.

Loading Datasets

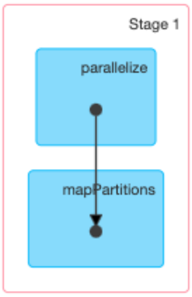
In the beforeAll() function, all three CSV files are read in as as DataFrames then compressed to Parquet format and persisted in external storage. A check is made to determine if the Parquet files exist on disk before running a test. If the files already exist, then they will be reused for all subsequent tests. Otherwise, they will be regenerated. Through the use of Parquet, our data will be stored in a compressed columnar format, which will allow for faster read and write performance as compared to reading from CSV. The file size of the datasets when converted to Parquet, are significantly smaller as compared to the original CSV files. For example, the CSV file for the NYC Motor Vehicle -Crashes was 369 MB and was reduced to 75.7 MB when converted to Parquet. Additionally, the output Parquet files for the NYC Motor Vehicle - Vehicles dataset was partitioned by ZIP_CODE. By doing this, the data is physically laid out on the filesystem in an order that will be the most efficient for performing our queries.

Some data preparation was needed before converting to Parquet, which includes the following.

- For all DataFrames, the whitespace between columns names needed to be replaced with underscores to avoid the invalid character errors when converting to Parquet. E.g., from CRASH TIME to CRASH_TIME.
- The data types of several columns in the NYC Motor Vehicle - Crashes dataset needed to be cast from a string to an integer type because they are used for numerical calculations in our query.

The below Directed acyclic graph (DAG) shows the operations performed when reading a parquet file. This operation is performed each time a test runs. Spark performs a parallelize operation followed by a mapPartitions operation.

▾ DAG Visualization

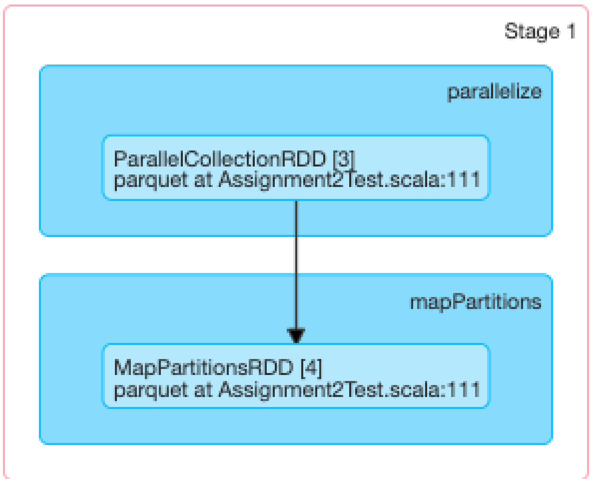


▾ **Completed Stages (1)**

Stage Id ▾	Description	Submitted	Duration
1	parquet at Assignment2Test.scala:111 +details	2020/05/09 19:12:59	0.6 s

Total Time Across All Tasks: 0.6 s
Locality Level Summary: Process local: 1

▾ DAG Visualization



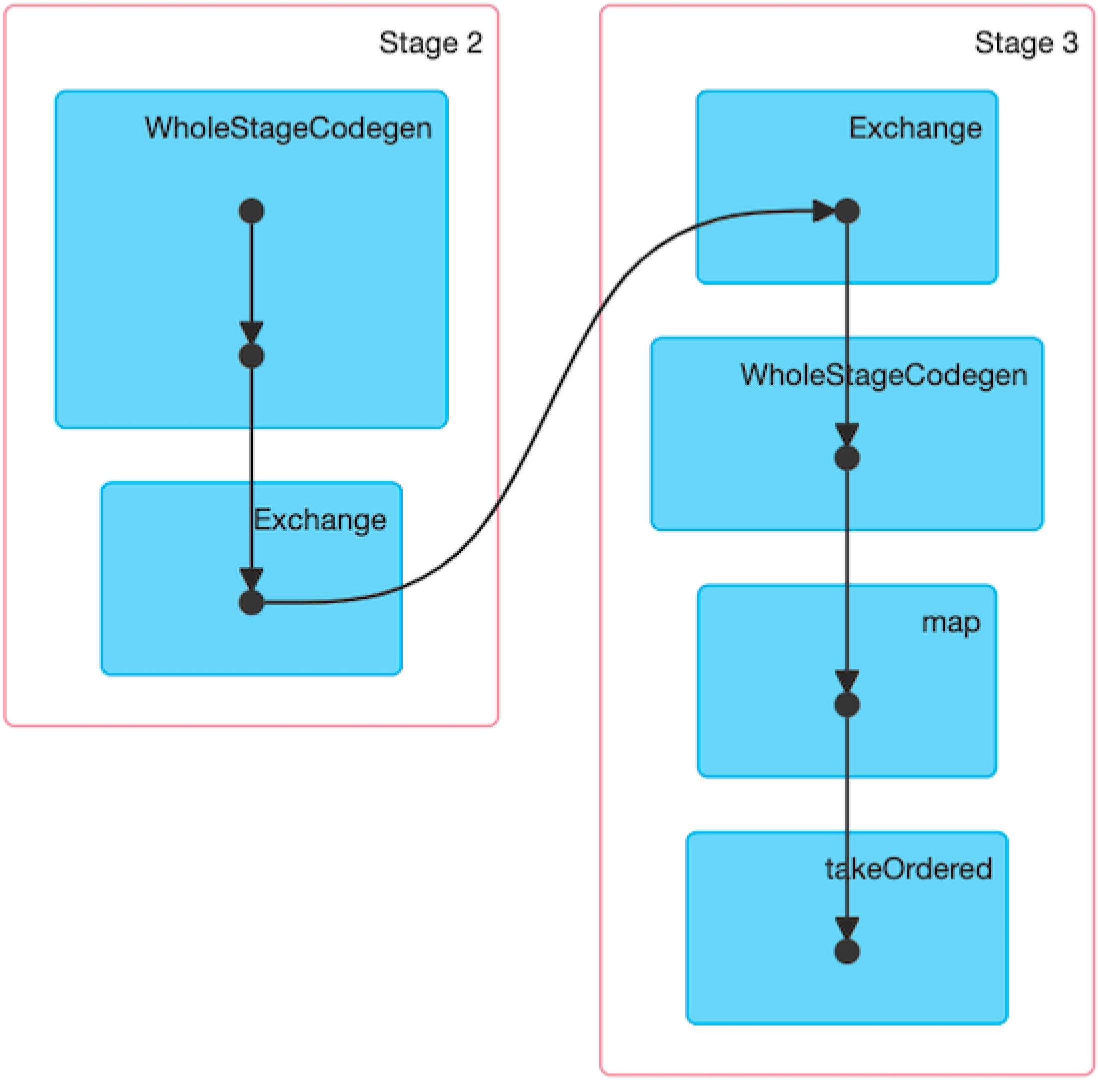
Analytic Questions

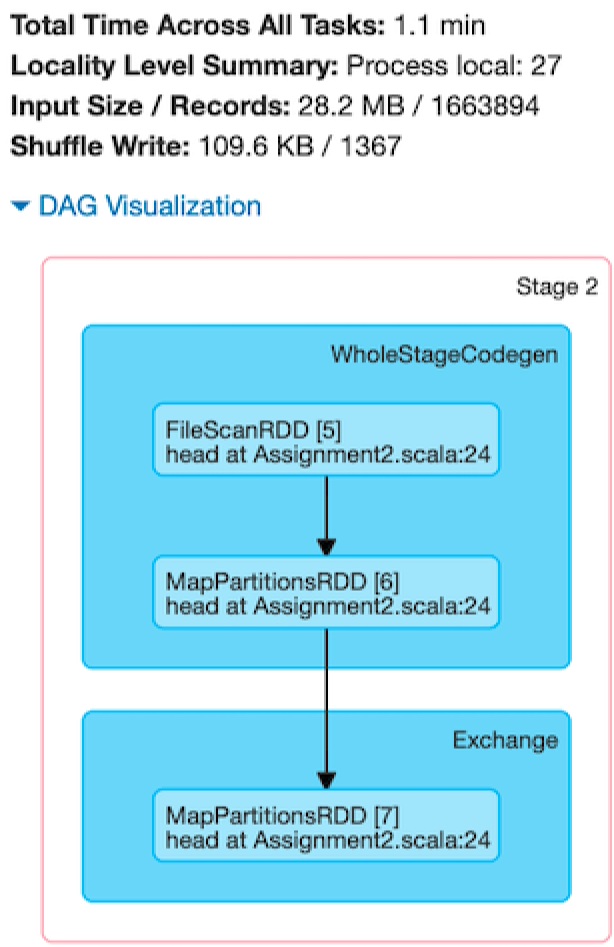
1. What are the top five most frequent contributing factors for accidents in NYC?

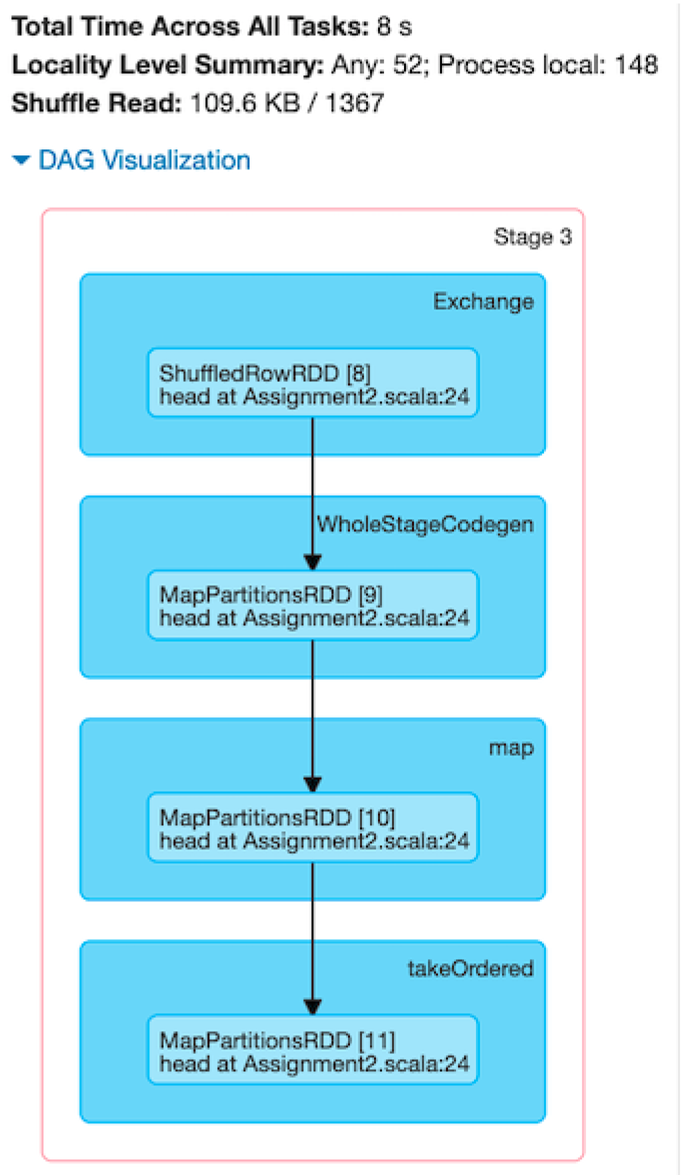
For this test, we first filtered out rows with an unspecified contributing factor. Next, we perform a groupBy CONTRIBUTING_FACTOR_VEHICLE_1, then count the number of occurrences of each contributing factor. Finally, we order by count and get the top 5 contributing factors.

Spark Internal Analysis

There are four stages that occur for this problem. In stage 0, we get the listing leaf files and directory for 234 paths, which are the different paths that were created when we partitioned the NYC Motor Vehicle Collisions - Crashes DataFrame by "ZIP_CODE". Each path represents a different ZIP_CODE. Next, in stage 1, we read the Parquet file from disk or memory if it is cached (as seen in the previous section). In our case, we are caching the parquet file for our DataFrame. The RDDs created in stage 1 are a parrallelCollectionRDD followed by a mapPartitionsRDD. Next, in stage 2 a FileScanRDD is created, followed by a MapPartitionRDD, then another MapParitionsRDD. In stage 3 a shuffledRowRDD is created because we are performing a group by which is a wide transformation, and thus data is shuffled across the cluster of nodes. Next, a MapPartitionsRDD is created, followed by another mapPartitionsRDD in the map step. The map function uses a narrow transformation, so the computations do not need to be shuffled across the cluster.







2. What percentage of accidents had alcohol as a contributing factor?

For this test, we first got the count of total accidents and stored in a val numTotalAccidents. Next, we filtered out accidents where alcohol involvement was a contributing factor for any of the vehicles involved in the accident and stored the result in numAlcoholRelatedAccidents. Finally, we performed the following calculation to get the percentage.

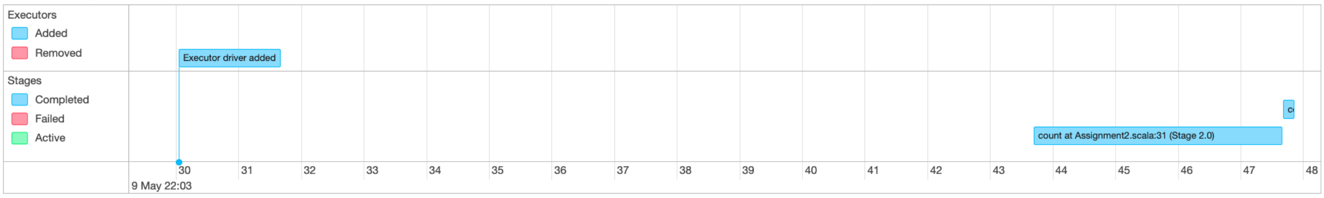
```
(numAlcoholRelatedAccidents * 100) / numTotalAccidents.toDouble
```

Spark Internal Analysis

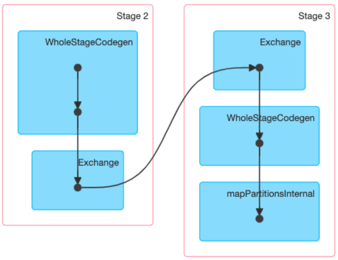
The data in stage 2 was split into 27 partitions, each executing a task. However, the data in stage 3 is only executing on a single partition.

Event Timeline

Enable zooming

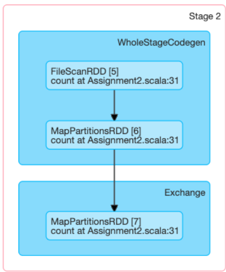


DAG Visualization



Completed Stages (2)

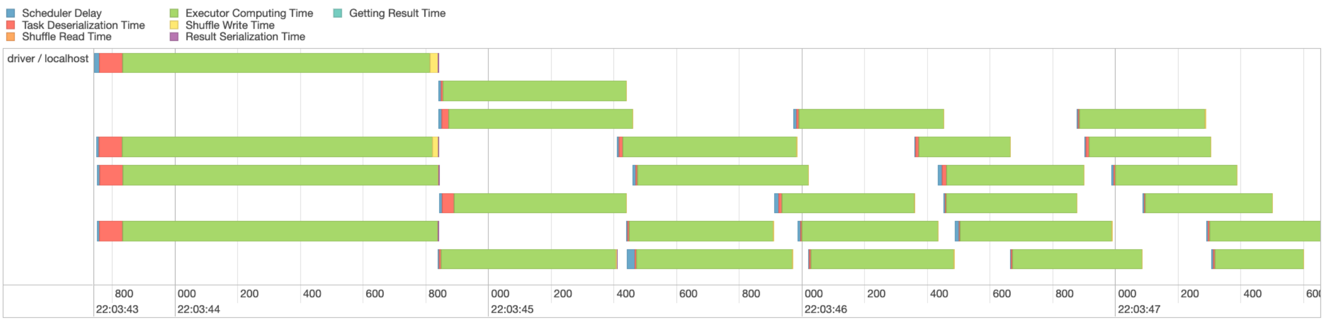
Stage Id ▾	Description	Submitted	Duration	Tasks: Succeeded/Total	Input	Output	Shuffle Read	Shuffle Write
3	count at Assignment2.scala:31 +details	2020/05/09 22:03:47	0.2 s	1/1			1592.0 B	
2	count at Assignment2.scala:31 +details	2020/05/09 22:03:43	4 s	27/27	12.4 MB			1592.0 B



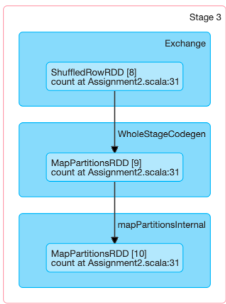
Show Additional Metrics

Event Timeline

Enable zooming



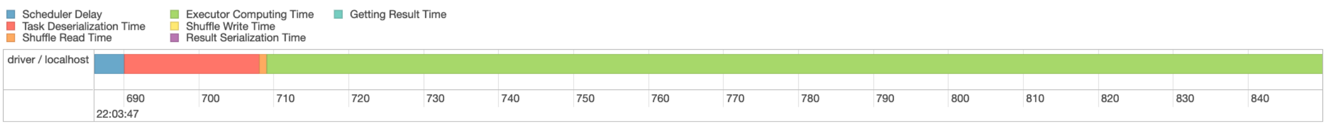
Summary Metrics for 27 Completed Tasks



Show Additional Metrics

Event Timeline

Enable zooming



Summary Metrics for 1 Completed Tasks

Metric	Min	25th percentile	Median	75th percentile	Max
Duration	0.1 s	0.1 s	0.1 s	0.1 s	0.1 s
GC Time	0 ms	0 ms	0 ms	0 ms	0 ms
Shuffle Read Size / Records	1592.0 B / 27	1592.0 B / 27	1592.0 B / 27	1592.0 B / 27	1592.0 B / 27

3. What time of day sees the most cyclist injures or deaths caused by a motor vehicle collision?

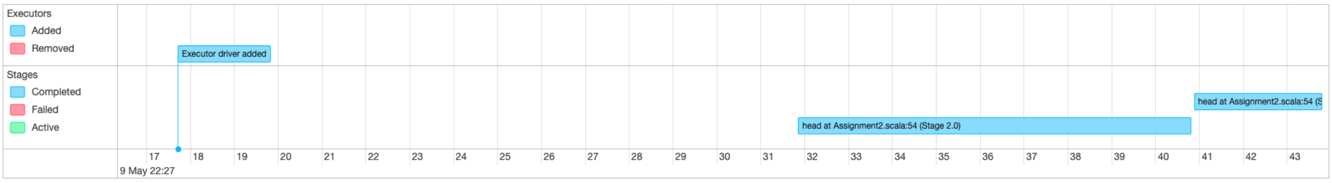
For this test, we first filter out accidents where there was at least one cyclist injury or fatality. Next, we perform a groupBy("CRASH_TIME") and counting the number of crashes for the various times throughout a 24 hour period. Finally, we order by count in descending order and get the top 3 times.

Spark Internal Analysis

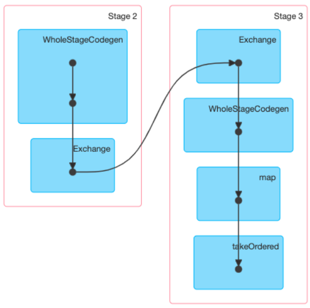
As we can see from stage 2, the tasks each took various amounts of time, some longer and some shorter. Additionally, towards the end of each task, a shuffle write was performed because the operation performed required a wide transformation. In this case, each task spends some time writing the results across the cluster. In total stage 2 took 1.1 minute to complete all of its 27 tasks. On the other hand, stage 3 executed over 200 tasks with a total time across all tasks of only 13 seconds. By this, we can tell that shuffling is costly when it comes to execution time, especially if we are processing large amounts of data.

▾ Event Timeline

☐ Enable zooming

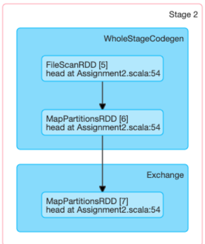


▾ DAG Visualization



▾ **Completed Stages (2)**

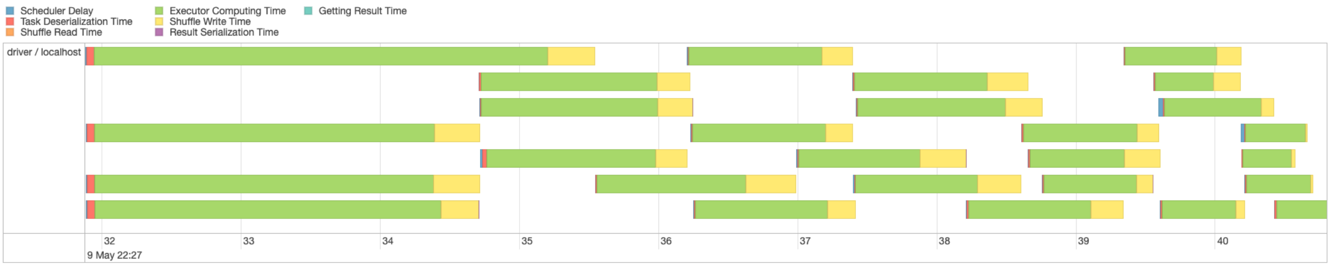
Stage Id ▾	Description	Submitted	Duration	Tasks: Succeeded/Total	Input	Output	Shuffle Read	Shuffle Write
3	head at Assignment2.scala:54 +details	2020/05/09 22:27:40	3 s	200/200			361.2 KB	
2	head at Assignment2.scala:54 +details	2020/05/09 22:27:31	9 s	27/27	57.0 MB			361.2 KB



▸ Show Additional Metrics

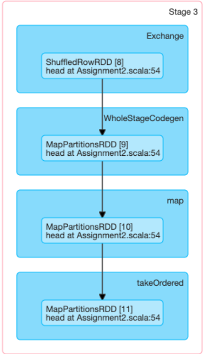
▾ Event Timeline

☐ Enable zooming

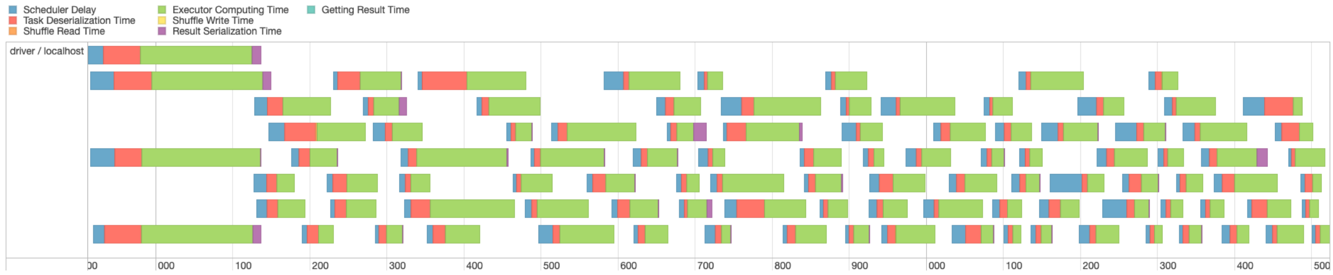


Summary Metrics for 27 Completed Tasks

Metric	Min	25th percentile	Median	75th percentile	Max
Duration	0.4 s	0.8 s	1 s	1 s	4 s
GC Time	0 ms	0 ms	13 ms	34 ms	0.2 s
Input Size / Records	580.7 KB / 44	1346.6 KB / 15036	2.2 MB / 42884	2.9 MB / 70449	4.0 MB / 590849



▸ Show Additional Metrics
▾ Event Timeline
☐ Enable zooming



Summary Metrics for 200 Completed Tasks

Metric	Min	25th percentile	Median	75th percentile	Max
Duration	8 ms	16 ms	29 ms	45 ms	0.2 s
GC Time	0 ms	0 ms	0 ms	0 ms	5 ms
Shuffle Read Size / Records	284.0 B / 4	1567.0 B / 34	1880.0 B / 48	2.2 KB / 69	3.0 KB / 125

▾ **Aggregated Metrics by Executor**

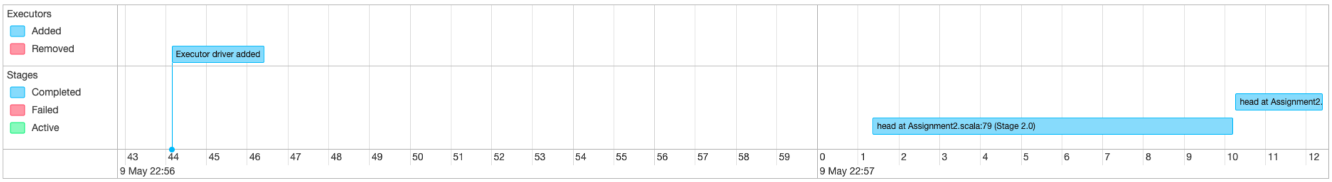
Executor ID ▴	Address	Task Time	Total Tasks	Failed Tasks	Killed Tasks	Succeeded Tasks	Shuffle Read Size / Records	Blacklisted
driver	192.168.1.10:60591	12 s	200	0	0	200	361.2 KB / 10350	false

4. Which zip code had the largest number of nonfatal and fatal accidents?

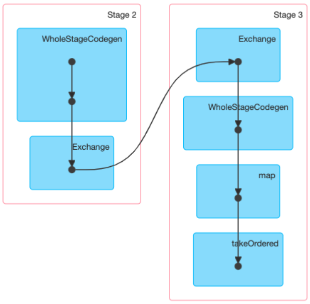
Find the zip code with the most significant number of nonfatal and fatal accidents required several steps. First, remove rows with null zip codes. Next, create a new column "TOTAL_INJURED_OR_KILLED", which is the sum of all nonfatal and fatal injuries for each accident. Next, get the total number of nonfatal and fatal injuries per zip code by first performing a group by zip code. Then use the agg and sum functions to sum up the values in the TOTAL_INJURED_OR_KILLED column per zip code. Afterward, store the computed output per zip code in a column aliased as TOTAL_INJURIES_AND_FATALITIES. Finally, order the results by TOTAL_INJURIES_AND_FATALITIES in descending order and get the top 3.

Spark Internal Analysis

Since we are calling the filter function right after loading the dataset, Spark performed a predicate pushdown, where it pushed the filter function down to the data source and performed the filter query before returning the result to the driver. A predicate pushdown improves query performance because filtering is done before loading the dataset in the driver, so less data is returned.

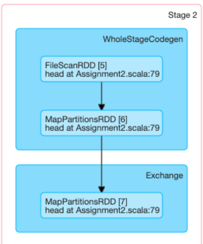


DAG Visualization



Completed Stages (2)

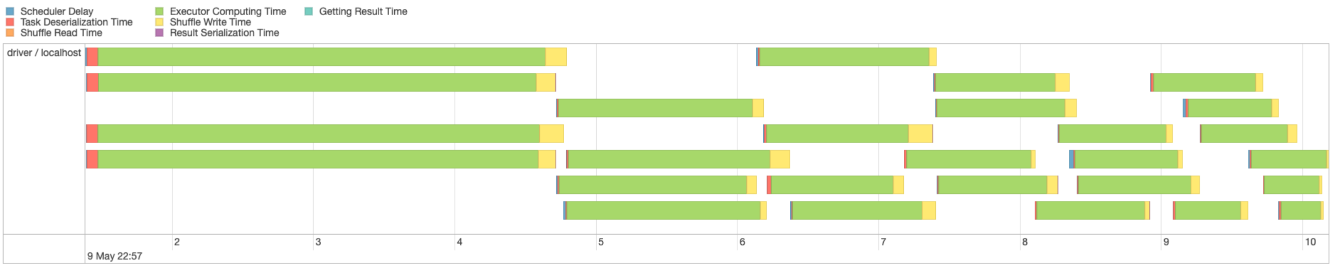
Stage Id	Description	Submitted	Duration	Tasks: Succeeded/Total	Input	Output	Shuffle Read	Shuffle Write
3	head at Assignment2.scala:79 +details	2020/05/09 22:57:10	2 s	200/200			43.7 KB	
2	head at Assignment2.scala:79 +details	2020/05/09 22:57:01	9 s	27/27	29.1 MB			43.7 KB



Show Additional Metrics

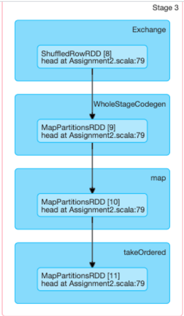
Event Timeline

Enable zooming

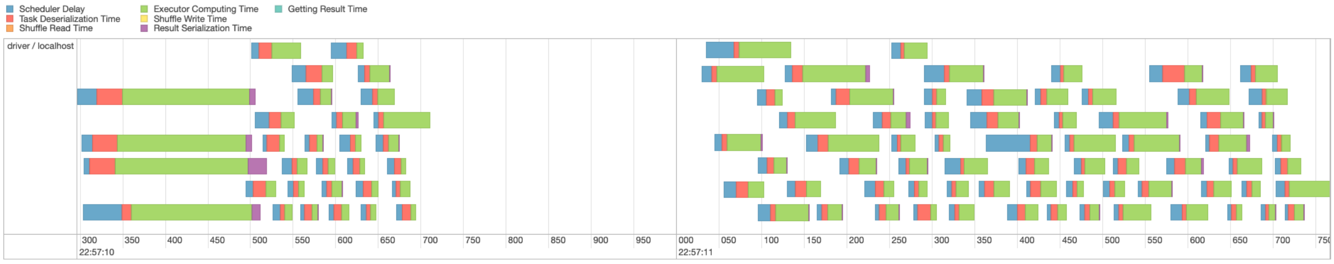


Summary Metrics for 27 Completed Tasks

Metric	Min	25th percentile	Median	75th percentile	Max
Duration	0.3 s	0.8 s	0.9 s	1 s	3 s
GC Time	3 ms	9 ms	14 ms	24 ms	94 ms
Input Size / Records	427.8 KB / 29	845.6 KB / 13653	1114.4 KB / 43149	1365.0 KB / 70152	1748.8 KB / 105570

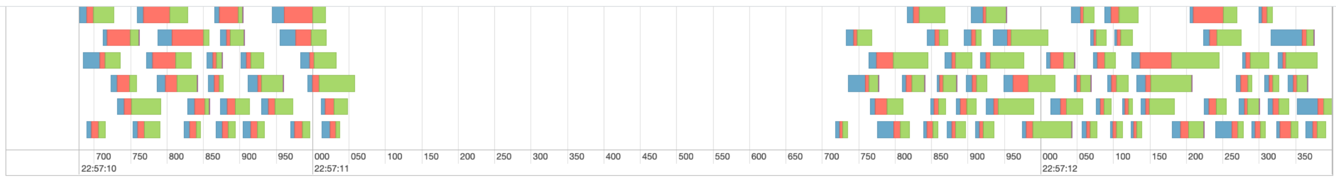


▸ Show Additional Metrics
▾ Event Timeline
Enable zooming



Summary Metrics for 200 Completed Tasks

Metric	Min	25th percentile	Median	75th percentile	Max
Duration	6 ms	10 ms	17 ms	28 ms	0.2 s



Summary Metrics for 200 Completed Tasks

Metric	Min	25th percentile	Median	75th percentile	Max
Duration	6 ms	10 ms	17 ms	28 ms	0.2 s
GC Time	0 ms	0 ms	0 ms	0 ms	20 ms
Shuffle Read Size / Records	0.0 B / 0	0.0 B / 0	213.0 B / 3	355.0 B / 6	860.0 B / 15

▾ **Aggregated Metrics by Executor**

Executor ID ▲	Address	Task Time	Total Tasks	Failed Tasks	Killed Tasks	Succeeded Tasks	Shuffle Read Size / Records	Blacklisted
driver	192.168.1.10:64089	9 s	200	0	0	200	43.7 KB / 667	false

▾ **Tasks (200)**

Page: < 1 2 — 2 Pages. Jump to 2 . Show 100 items in a page. Go

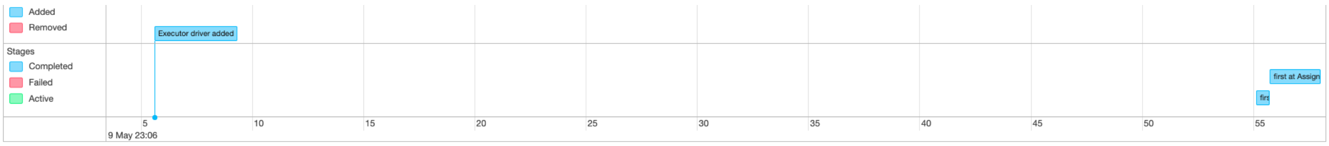
Index ▲	ID	Attempt	Status	Locality Level	Executor ID	Host	Launch Time	Duration	GC Time	Shuffle Read Size / Records	Errors
100	397	0	SUCCESS	ANY	driver	localhost	2020/05/09 22:57:11	7 ms		213.0 B / 3	
101	293	0	SUCCESS	PROCESS_LOCAL	driver	localhost	2020/05/09 22:57:10	28 ms		0.0 B / 0	
102	398	0	SUCCESS	ANY	driver	localhost	2020/05/09 22:57:11	77 ms		426.0 B / 6	
103	399	0	SUCCESS	ANY	driver	localhost	2020/05/09 22:57:11	21 ms		497.0 B / 7	
104	400	0	SUCCESS	ANY	driver	localhost	2020/05/09 22:57:11	13 ms		213.0 B / 3	
105	401	0	SUCCESS	ANY	driver	localhost	2020/05/09 22:57:11	48 ms		284.0 B / 4	
106	294	0	SUCCESS	PROCESS_LOCAL	driver	localhost	2020/05/09 22:57:10	21 ms		0.0 B / 0	
107	295	0	SUCCESS	PROCESS_LOCAL	driver	localhost	2020/05/09 22:57:10	10 ms		0.0 B / 0	
108	402	0	SUCCESS	ANY	driver	localhost	2020/05/09 22:57:11	22 ms		140.0 B / 2	
109	296	0	SUCCESS	PROCESS_LOCAL	driver	localhost	2020/05/09 22:57:10	18 ms		0.0 B / 0	
110	403	0	SUCCESS	ANY	driver	localhost	2020/05/09 22:57:11	13 ms		284.0 B / 4	
111	404	0	SUCCESS	ANY	driver	localhost	2020/05/09 22:57:11	18 ms		284.0 B / 4	
112	405	0	SUCCESS	ANY	driver	localhost	2020/05/09 22:57:11	36 ms		142.0 B / 2	
113	406	0	SUCCESS	ANY	driver	localhost	2020/05/09 22:57:11	7 ms		142.0 B / 2	
114	407	0	SUCCESS	ANY	driver	localhost	2020/05/09 22:57:11	12 ms		314.0 B / 6	

5. Which vehicle make, model, and year was involved in the most accidents?

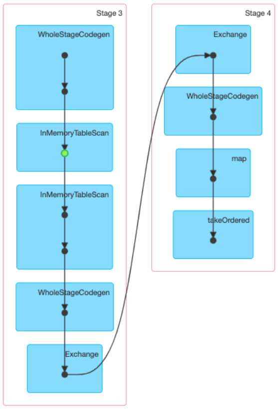
To determine which vehicle make, model, and year was involved in the most accidents, we first remove any rows where the vehicle make, model, and year is null. Next, we did a groupBy("VEHICLE_MAKE", "VEHICLE_MODEL", "VEHICLE_YEAR"), then count and sort by descending order and get the first value, which is the most accidents. Likewise, to get the least accidents, we did the same previous steps but sort by ascending order and got the first value.

Spark Internal Analysis

Similar to test 4, test 5 is also performing a filter as the first function in the test, so Spark performed a predicate pushdown as well. Additionally, in stage 3, we reused the cached RDD that was created from performing a previous transformation. Reusing the cached RDD allowed for faster access time in future actions that needed to use the same data.

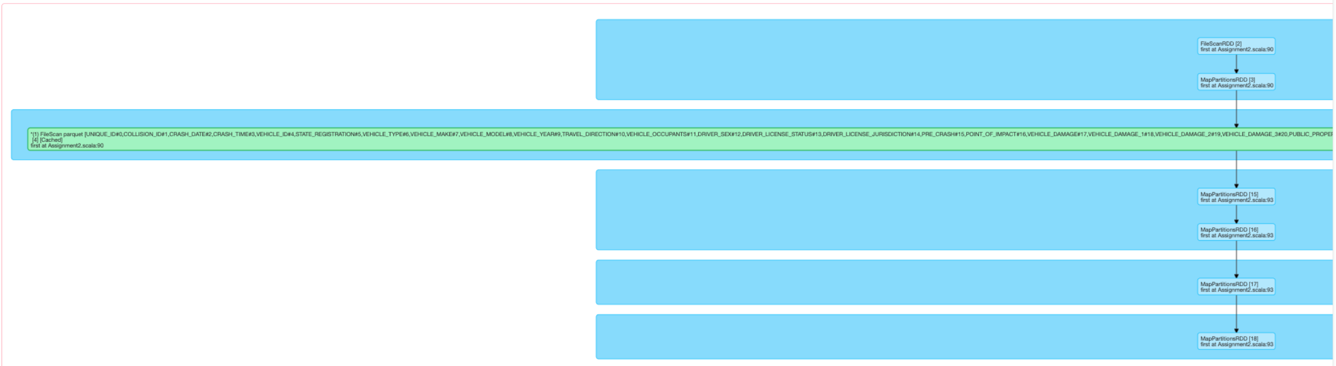


DAG Visualization



Completed Stages (2)

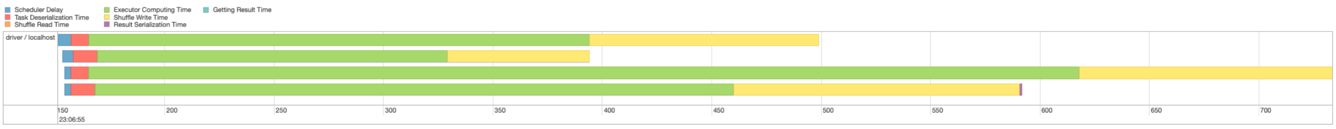
Stage Id	Description		Submitted	Duration	Tasks: Succeeded/Total	Input	Output	Shuffle Read	Shuffle Write
4	first at Assignment2.scala:93	+details	2020/05/09 23:06:55	2 s	200/200			400.8 KB	
3	first at Assignment2.scala:93	+details	2020/05/09 23:06:55	0.6 s	4/4	304.0 MB			400.8 KB



Show Additional Metrics

Event Timeline

Enable zooming

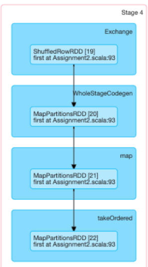


Summary Metrics for 4 Completed Tasks

Metric	Min	25th percentile	Median	75th percentile	Max
Duration	0.2 s	0.3 s	0.4 s	0.6 s	0.6 s
GC Time	8 ms	8 ms	8 ms	8 ms	8 ms
Input Size / Records	56.0 MB / 57	56.1 MB / 57	83.4 MB / 96	108.5 MB / 127	108.5 MB / 127
Shuffle Write Size / Records	4.0 KB / 43	5.4 KB / 57	174.9 KB / 6015	216.6 KB / 7551	216.6 KB / 7551

Aggregated Metrics by Executor

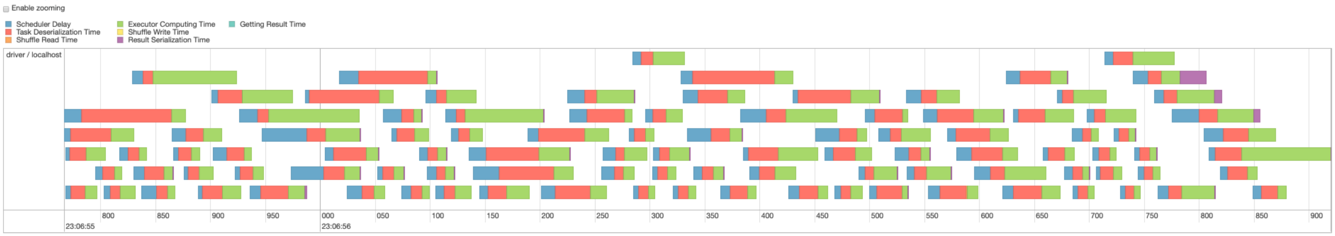
Executor ID	Address	Task Time	Total Tasks	Failed Tasks	Killed Tasks	Succeeded Tasks	Input Size / Records	Shuffle Write Size / Records	Blacklisted
driver	192.168.1.10:65173	2 s	4	0	0	4	304.0 MB / 337	400.8 KB / 13666	false



Show Additional Metrics

Event Timeline

Enable zooming



Summary Metrics for 200 Completed Tasks

Metric	Min	25th percentile	Median	75th percentile	Max
Duration	5 ms	8 ms	13 ms	21 ms	0.1 s
GC Time	0 ms	0 ms	0 ms	0 ms	7 ms
Shuffle Read Size / Records	1481.0 B / 48	1856.0 B / 60	2.0 KB / 68	2.2 KB / 75	2.7 KB / 96

6. How do the number of collisions in an area of NYC correlate to the number of trees in the area?

We used the NYC motor vehicle collisions - crashes and 2015 NYC tree census datasets for this test. We first rename the postcode column to ZIP_CODE on the treeCensus DataFrame. Next, we perform a groupBy on the treeCensus DataFrame to get the number of trees per zip code. We also performed a groupBy on the collisions DataFrame to get the number of accidents per zip code. Finally, we did an inner equi-join of the collisions DataFrame with the treeCensus DataFrame using the "ZIP_CODE" collumn. Then finally, ordered by "TOTAL_CRASHES" in descending order.

Spark Internal Analysis

The previous tests only needed to load a single DataFrame and had two to three parquet jobs per test. However, this test uses two DataFrames and thus required a third parquet job to read the additional data. In stage 5, the renaming of the postcode column is performed, followed by the groupBy on the treeCensus DataFrame which reused the cached treeCensus data. This test also used a join function, which performs a wide transformation, and therefore shuffling was needed.

Spark Jobs (?)

User: Devin
Total Uptime: 1.3 min
Scheduling Mode: FIFO
Completed Jobs: 5

▸ Event Timeline

▾ Completed Jobs (5)

Job Id ▾	Description	Submitted	Duration	Stages: Succeeded/Total	Tasks (for all stages): Succeeded/Total
4	head at Assignment2.scala:116 head at Assignment2.scala:116	2020/05/09 23:20:53	8 s	2/2	227/227
3	run at ThreadPoolExecutor.java:1128 run at ThreadPoolExecutor.java:1128	2020/05/09 23:20:25	28 s	2/2	204/204
2	parquet at Assignment2Test.scala:123 parquet at Assignment2Test.scala:123	2020/05/09 23:20:21	93 ms	1/1	1/1
1	parquet at Assignment2Test.scala:111 parquet at Assignment2Test.scala:111	2020/05/09 23:20:17	0.7 s	1/1	1/1
0	Listing leaf files and directories for 234 paths: file:/Users/Devin/Documents/IdeaProjects/spark-assignment-2/data/NYC_Motor_Vehicle_Collisions_Crashes.parquet/zip_code=10069, ... parquet at Assignment2Test.scala:111	2020/05/09 23:20:12	5 s	1/1	234/234

Stages for All Jobs

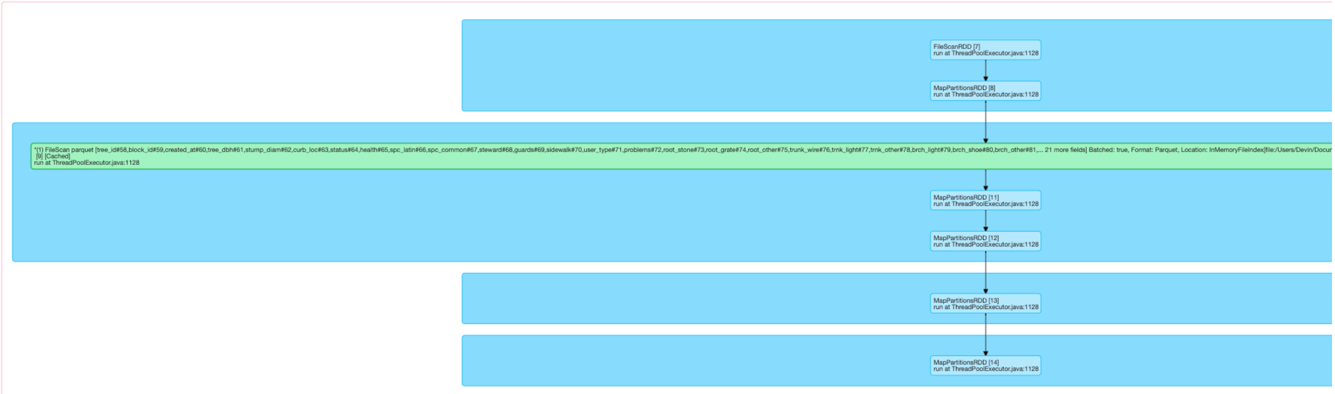
Completed Stages: 7

▾ Completed Stages (7)

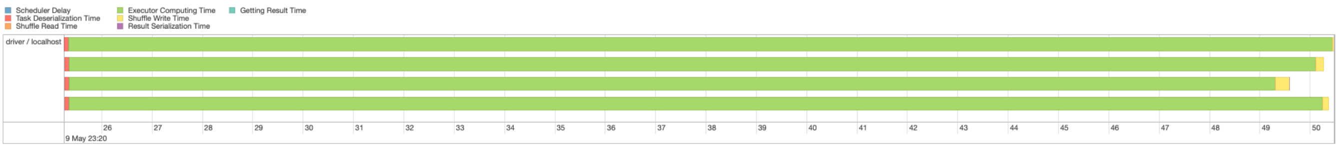
Stage Id ▾	Description	Submitted	Duration	Tasks: Succeeded/Total	Input	Output	Shuffle Read	Shuffle Write
6	head at Assignment2.scala:116 +details	2020/05/09 23:20:59	2 s	200/200			44.4 KB	
5	head at Assignment2.scala:116 +details	2020/05/09 23:20:53	5 s	27/27	12.3 MB			44.4 KB
4	run at ThreadPoolExecutor.java:1128 +details	2020/05/09 23:20:50	3 s	200/200			32.1 KB	
3	run at ThreadPoolExecutor.java:1128 +details	2020/05/09 23:20:25	25 s	4/4	58.0 MB			32.1 KB
2	parquet at Assignment2Test.scala:123 +details	2020/05/09 23:20:21	41 ms	1/1				
1	parquet at Assignment2Test.scala:111 +details	2020/05/09 23:20:17	0.6 s	1/1				
0	Listing leaf files and directories for 234 paths: file:/Users/Devin/Documents/IdeaProjects/spark-assignment-2/data/NYC_Motor_Vehicle_Collisions_Crashes.parquet/zip_code=10069, ... parquet at Assignment2Test.scala:111 +details	2020/05/09 23:20:12	4 s	234/234				

Total Time Across All Tasks: 1.7 min
Locality Level Summary: Process local: 4
Input Size / Records: 58.0 MB / 683788
Shuffle Write: 32.1 KB / 730

▾ DAG Visualization



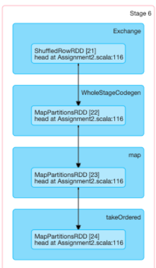
▸ Show Additional Metrics
▾ Event Timeline
Enable zooming



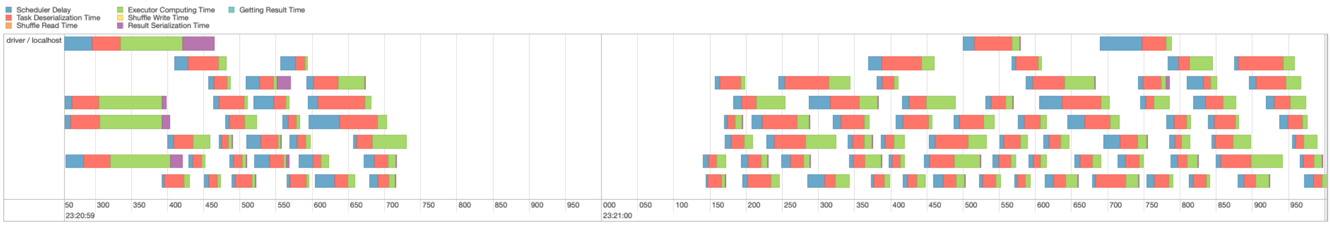
Details for Stage 6 (Attempt 0)

Total Time Across All Tasks: 3 s
Locality Level Summary: Any: 134; Process local: 66
Shuffle Read: 44.4 KB / 667

▾ DAG Visualization



▸ Show Additional Metrics
▾ Event Timeline
Enable zooming



Summary Metrics for 200 Completed Tasks

Metric	Min	25th percentile	Median	75th percentile	Max
Duration	4 ms	6 ms	11 ms	17 ms	87 ms
GC Time	0 ms	0 ms	0 ms	0 ms	12 ms

The code ran on a single executor with 4 RDD Blocks, 4 cores CPU, and 1.1 GB RAM.

Executors

▸ Show Additional Metrics

Summary

	RDD Blocks	Storage Memory	Disk Used	Cores	Active Tasks	Failed Tasks	Complete Tasks	Total Tasks	Task Time (GC Time)	Input	Shuffle Read	Shuffle Write	Blacklisted
Active(1)	4	86.4 MB / 1.1 GB	0.0 B	4	0	0	667	667	2.7 min (4 s)	73.7 MB	78.4 KB	78.4 KB	0
Dead(0)	0	0.0 B / 0.0 B	0.0 B	0	0	0	0	0	0 ms (0 ms)	0.0 B	0.0 B	0.0 B	0
Total(1)	4	86.4 MB / 1.1 GB	0.0 B	4	0	0	667	667	2.7 min (4 s)	73.7 MB	78.4 KB	78.4 KB	0

Executors

Show 20 entries   Search:

Executor ID	Address	Status	RDD Blocks	Storage Memory	Disk Used	Cores	Active Tasks	Failed Tasks	Complete Tasks	Total Tasks	Task Time (GC Time)	Input	Shuffle Read	Shuffle Write	Thread Dump
driver	192.168.1.10:50417	Active	4	86.4 MB / 1.1 GB	0.0 B	4	0	0	667	667	2.7 min (4 s)	73.7 MB	78.4 KB	78.4 KB	Thread Dump

Showing 1 to 1 of 1 entries   Previous 1 Next

Since we are caching the Parquet files for both the collisions and treeCensus DataFrames, an RDD is created for each dataset and persisted to memory for reuse during subsequent actions in the test. The transformed RDD for the treeCensus data is cached into 4 partitions and uses 82.3 MB in RAM storage. Additionally, the transformed RDD for the collisions data is cached into 27 partitions and takes up 154.8 MB in RAM storage. Because Sparks transformations are lazy, the transformations will not execute until an action is performed on it. However, by adding caching, we are ensuring that when actions are executed on transformations that use the same data, that we are reusing the previously processed data vs. having to reload the data.

Storage

RDDs

ID	RDD Name	Storage Level	Cached Partitions	Fraction Cached	Size in Memory	Size on Disk
9	*(1) FileScan parquet [tree_id#203,block_id#204,created_at#205,tree_dbh#206,stump_diam#207,curb_loc#208,status#209,health#210,spc_latin#211,spc_common#212,steward#213,guards#214,sidewalk#215,user_type#216,problems#217,root_stone#218,root_grate#219,root_other#220,trunk_wire#221,trnk_light#222,trnk_other#223,brch_light#224,brch_shoe#225,brch_other#226,... 21 more fields] Batched: true, Format: Parquet, Location: InMemoryFileIndex[file:/Users/Devin/Documents/IdeaProjects/spark-assignment-2/data/NYC_2015_Stree..., PartitionFilters: [], PushedFilters: [], ReadSchema: struct<tree_id:int,block_id:int,created_at:string,tree_dbh:int,stump_diam:int,curb_loc:string,sta...	Memory Deserialized 1x Replicated	4	100%	82.3 MB	0.0 B
20	*(1) FileScan parquet [CRASH_DATE#0,CRASH_TIME#1,BOROUGH#2,LATITUDE#3,LONGITUDE#4,LOCATION#5,ON_STREET_NAME#6,CROSS_STREET_NAME#7,OFF_STREET_NAME#8,NUMBER_OF_PERSONS_INJURED#9,NUMBER_OF_PERSONS_KILLED#10,NUMBER_OF_PEDESTRIANS_INJURED#11,NUMBER_OF_PEDESTRIANS_KILLED#12,NUMBER_OF_CYCLIST_INJURED#13,NUMBER_OF_CYCLIST_KILLED#14,NUMBER_OF_MOTORIST_INJURED#15,NUMBER_OF_MOTORIST_KILLED#16,CONTRIBUTING_FACTOR_VEHICLE_1#17,CONTRIBUTING_FACTOR_VEHICLE_2#18,CONTRIBUTING_FACTOR_VEHICLE_3#19,CONTRIBUTING_FACTOR_VEHICLE_4#20,CONTRIBUTING_FACTOR_VEHICLE_5#21,COLLISION_ID#22,VEHICLE_TYPE_CODE_1#23,... 5 more fields] Batched: true, Format: Parquet, Location: InMemoryFileIndex[file:/Users/Devin/Documents/IdeaProjects/spark-assignment-2/data/NYC_Motor_Vehi..., PartitionCount: 234, PartitionFilters: [], PushedFilters: [], ReadSchema: struct<CRASH_DATE:string,CRASH_TIME:string,BOROUGH:string,LATITUDE:double,LONGITUDE:double,LOCATI...	Memory Deserialized 1x Replicated	27	100%	154.8 MB	0.0 B

Project Overview

- Language: Scala
- Framework: Apache Spark
- Build tool: SBT
- Testing Framework: Scalatest

Running Tests

From Intellij

Right click on `ExampleDriverTest` and choose `Run 'ExampleDriverTest'`

From the command line

On Unix systems, test can be run:

```
$ ./sbt test
```

or on Windows systems:

```
C:\> ./sbt.bat test
```

Configuring Logging

Spark uses log4j 1.2 for logging. Logging levels can be configured in the file `src/test/resources/log4j.properties`

Spark logging can be verbose, for example, it will tell you when each task starts and finishes as well as resource cleanup messages. This isn't always useful or desired during regular development. To reduce the verbosity of logs, change the line `log4j.logger.org.apache.spark=INFO` to `log4j.logger.org.apache.spark=WARN`

Scala Worksheets

The worksheet `src/test/scala/com/spark/example/playground.sc` is a good place to try out Scala code. Add your code to the left pane of the worksheet, click the 'play' button, and the result will display in the right pane.

Note: The worksheet will not work for Spark code.

Documentation

- RDD: https://spark.apache.org/docs/latest/rdd-programming-guide.html
- Batch Structured APIs: https://spark.apache.org/docs/latest/sql-programming-guide.html

References

[1] National Highway Traffic Safety Administration. “NCSA Publications & Data Requests.” Early Estimate of Motor Vehicle Traffic Fatalities for the First Quarter of 2019, 2019, https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812783.

[2] (NYPD), Police Department. “Motor Vehicle Collisions - Crashes: NYC Open Data.” Motor Vehicle Collisions - Crashes | NYC Open Data, 8 May 2020, data.cityofnewyork.us/Public-Safety/Motor-Vehicle-Collisions-Crashes/h9gi-nx95.

[3] (NYPD), Police Department. “Motor Vehicle Collisions - Vehicles: NYC Open Data.” Motor Vehicle Collisions - Vehicles | NYC Open Data, 8 May 2020, data.cityofnewyork.us/Public-Safety/Motor-Vehicle-Collisions-Vehicles/bm4k-52h4.

[4] Department of Parks and Recreation. “2015 Street Tree Census - Tree Data: NYC Open Data.” 2015 Street Tree Census - Tree Data | NYC Open Data, 4 Oct. 2017, data.cityofnewyork.us/Environment/2015-Street-Tree-Census-Tree-Data/uvpi-gqnh.