Analysis of Parking Violations in New York City

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Motivation and Project Description

- Cities have obscured parking laws aimed to make big profits.
- In 2015, NYC collected $565 million in traffic and parking penalties.
- Most parking tickets are given out in high quantities and cost over $100.

Our Big Data Application:

- To reduce chances of getting fined.
- Useful to know which types of vehicles more often get fined.
- Identify correlations between which types of vehicles received the costliest violations depending on the season.
  - types: registration state, plate type, vehicle body type, vehicle make, vehicle color, vehicle year
  - seasons: summer, fall, winter, spring
- Compare and contrast development process and performance between Hadoop MapReduce and PySpark.

Data Frameworks & Cloud Computing Platform

Frameworks:

- Apache Hadoop MapReduce.
- Apache Spark (PySpark interface).
- Apache Hue to view and analyze the results.

Platform:

- Cloudera virtual machine in pseudo-distributed mode.

Environments:

- Eclipse for Hadoop MapReduce.
- Basic text editor and Linux terminal for PySpark.

Dataset

- Contains parking violation data from NYC DMV.
- Approximately 9GB, across 4 CSV files.
- Around 42.3 million entries, each with 51 comma separated values.
- Columns gathered: vehicle body type, vehicle make, vehicle year, vehicle color, registration state, plate type, issue date, violation code.

CSV

Found on Kaggle: https://www.kaggle.com/new-york-city/nyc-parking-tickets

Hadoop MapReduce Components

Driver:

- Utilized ToolRunner with the argument “taskType”.
    - <taskType> = registrationState, plateType, vehicleBodyType, vehicleMake, vehicleColor, vehicleYear
- Utilized LocalJobRunner.
- Linked Mapper, Reducer, and Partitioner.
- Set reduce tasks to 4.
- All output types are of type “Text”.

```
        Map-Reduce Framework
                Map input records=40098
                Map output records=38905
                Map output bytes=598733
                Map output materialized bytes=676663
                Input split bytes=668
                Combine input records=0
                Combine output records=0
                Reduce input groups=554
                Reduce shuffle bytes=676663
                Reduce input records=38905
                Reduce output records=225
                Spilled Records=77810
                Shuffled Maps =20
                Failed Shuffles=0
                Merged Map outputs=20
                GC time elapsed (ms)=554
                CPU time spent (ms)=16210
                Physical memory (bytes) snapshot=1579941888
                Virtual memory (bytes) snapshot=8392187904
                Total committed heap usage (bytes)=935460864
        Shuffle Errors
                BAD_ID=0
                CONNECTION=0
                IO_ERROR=0
                WRONG_LENGTH=0
                WRONG_MAP=0
                WRONG_REDUCE=0
        File Input Format Counters
                Bytes Read=8147676
        File Output Format Counters
                Bytes Written=3850
Total execution time: 84320
[training@localhost ~]$
```

Partitioner:

- Parsed out the season from Mapper value.
- Distributed to one of the 4 Reducers (one for each season).

Hadoop MapReduce Components (cont.)

Mapper:

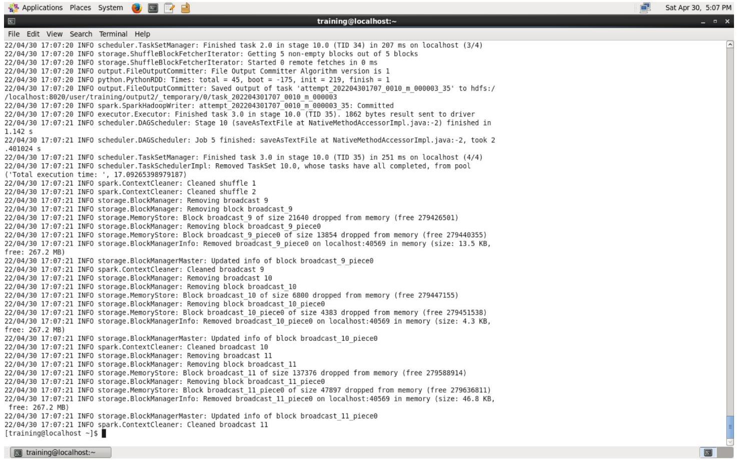
- Get <taskType> argument and validate it.
- Split line using regex and filter out lines with missing or misformatted data.
- Gather the <taskType>, “issueDate”, and “violationCode” columns.
- Translate “issueDate” month into a season.
- Emit pair (<taskType>, [season, violationCode]).

Reducer:

- Translate violation code into dollar amount.
- Accumulate count and total dollars, find average.
- Filter out keys with less than 5 values.
- Emit pair (<taskType>, [count, totalDollars, average]).

PySpark Components

- Used RDDs with transformations and actions.
- Gathered <task_type> data.
- Similar operations, but different order.
- Filter, map, reduceByKey, then partitionBy.
- Emit pair (<task_type>, [count, total_dollars, average]).



Registration State

- Minnesota, Indiana, Oklahoma, Idaho, New Jersey, Arizona, and Illinois had high ticket prices.
- Government plates and foreign plates (Canadian and Mexico) also had high violation costs.

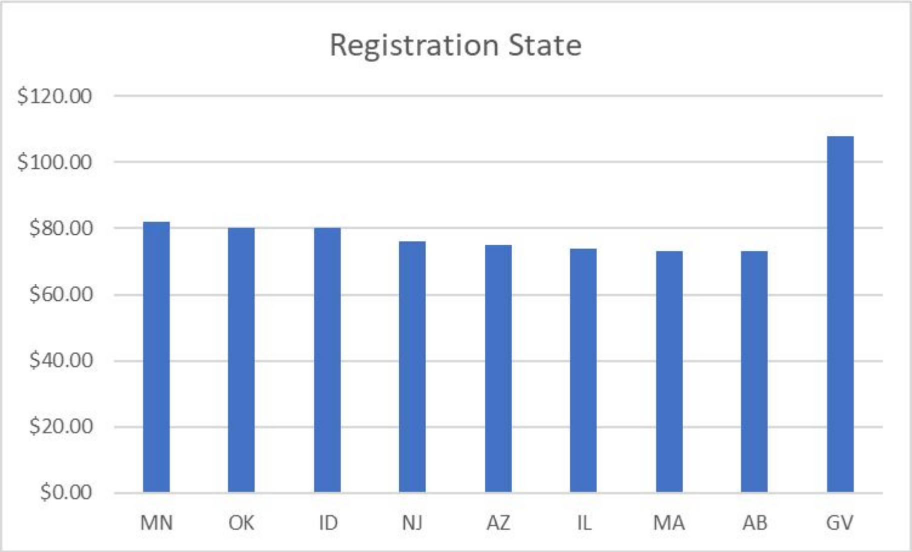
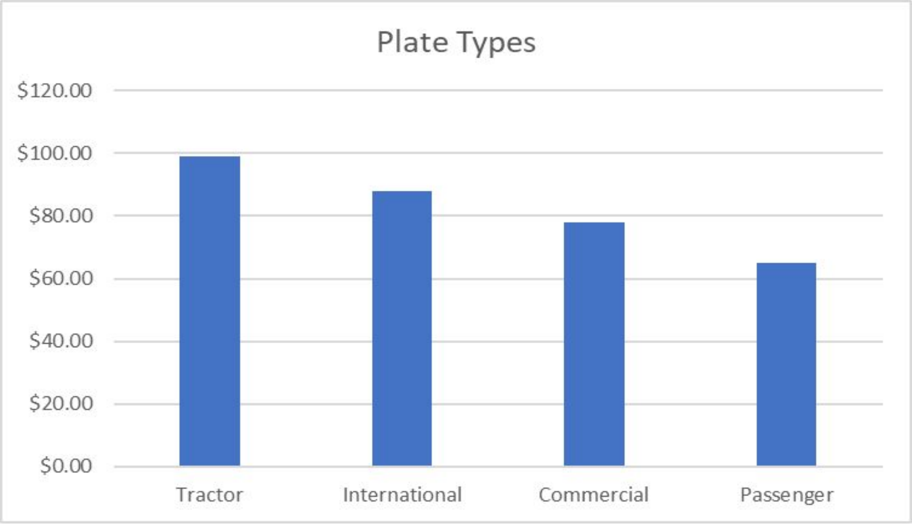


Plate type

- Passenger and commercial had the cheapest violations.
- Tractors, ATDs, and farm vehicles had the costliest violations.
- International and government plates also had high ticket prices.



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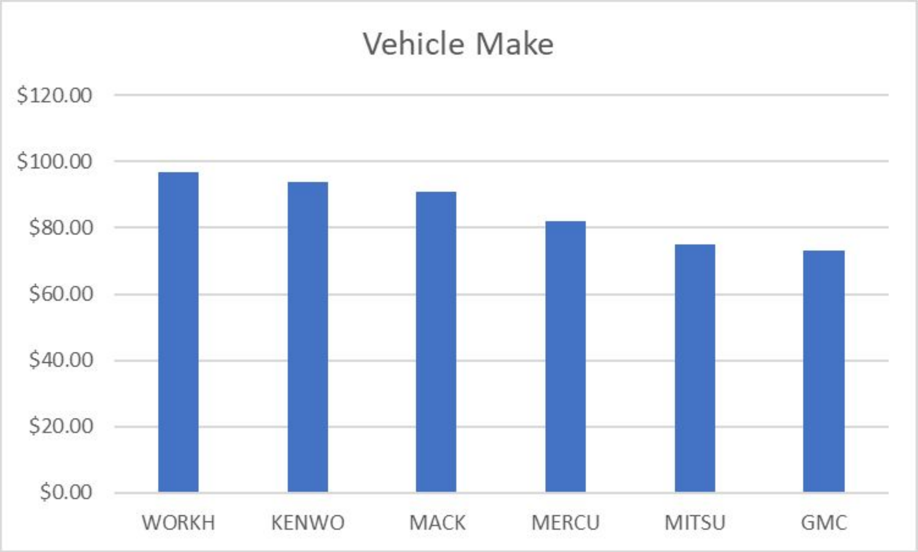
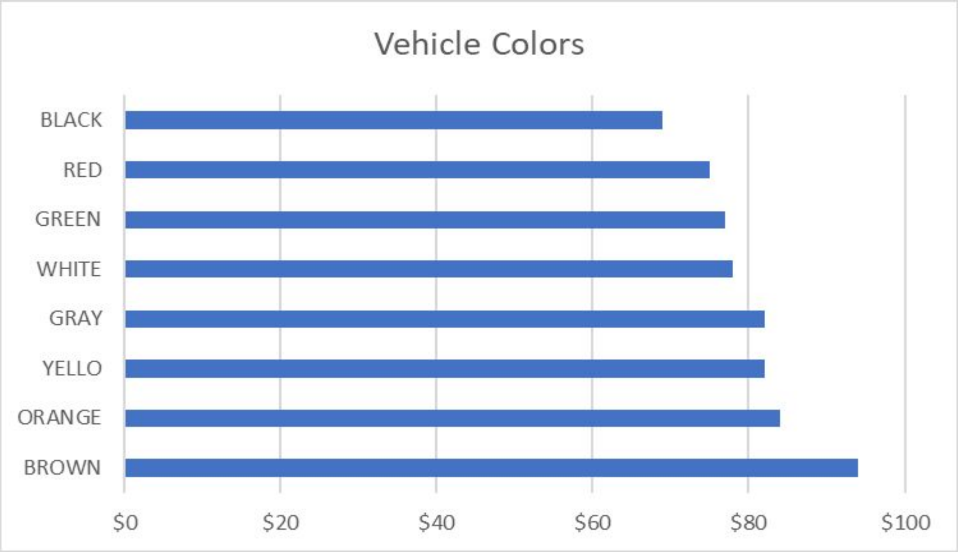
Vehicle Make

- Commercial vehicles brands were ticketed higher than passenger ones, such as Workhorse, Kentwood, and Mack.
- American based brands such as GMC, Mercury, Dodge, and Ford were ticketed higher than foreign made brands.



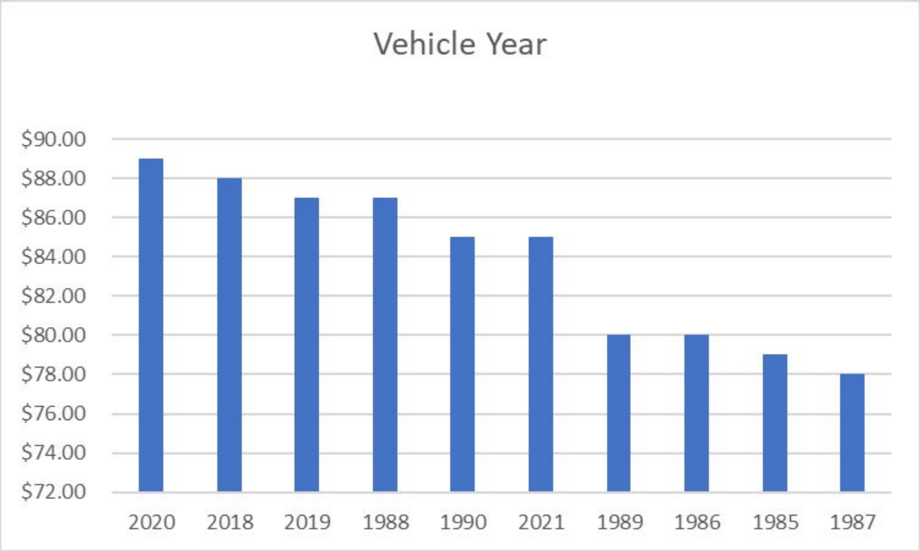
Vehicle Color

- Brown, orange, yellow, green, red, and multi-colored vehicles had higher violation costs.
- Among the three most popular colors (white, black, and gray), gray was the highest, then white, and finally black.



Vehicle Year

- New cars made from the 2010s had high ticket prices.
- Vehicles made between the years 1985-1997 correlated to a $10-$20 higher ticket price than those made before or after those years.



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Development Results

- Both develop in an Agile environment.

Hadoop MapReduce:

- LocalJobRunner made testing easier.
- Having 4 files was more tedious.
- Useful error messages.

PySpark:

- No IDE made for cumbersome environment.
- Chained operations was beneficial.
- Having only 1 file was easy.
- Difficult error messages.

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Performance Results

- PySpark was quicker than Hadoop MapReduce.

Hadoop MapReduce:

- Entire dataset: 2631.267 seconds
- Trimmed dataset: 84.32 seconds
- Slower due to many disk read and write operations.

```
Total execution time: 84320
[training@localhost ~]$
```

Spark:

- Entire dataset: 512.717 seconds
- Trimmed dataset: 17.093 seconds
- Faster due to in-memory read and write operations and lazy evaluation.

```
('Total execution time: ', 17.09265398979187
```

Conclusion

- Costlier tickets given out in winter and spring.
- PySpark development was easier and performed better than Hadoop MapReduce.
- Error messages were better in Hadoop MapReduce.

Challenges:

- Erroneous data.
- Unknown data and many alterations of the same key.
    - e.g., black was abbreviated as BLCK, BL, BK, BCK.
- Limited VM memory size and disk space.

Improvements:

- Filtering process.
- New distributed environment.