

Data Engineering Project Report

on

New York Cabs

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Authorship Details

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1 - Introduction

NYC Taxi tripwise data is being analysed for the month of June 2018 for the Yellow taxi

This project will give an insight on how to fetch data from CSV file, pass it through a Kafka pipeline and store it into a NoSQL Database (in our case MongoDB). MongoDb is then queried for analysis and visualization. Due to huge size of each CSV file and limited processing power on laptops, we selected and downloaded the Yellow Taxi (June) file (see section on Data Source for details).

The entire implementation is in a non-distributed environment on a single laptop.

Some basic questions are answered in the section on <u>Analysis and Visualisation</u> using parameters like fare, distance, passengers and payment method used for the trips. A derived field of trip duration is also used for analysis.

2 - Information on Data Source

New York City Taxi and Limousine Commission is a US Government agency responsible for licensing and regulating over 50,000 vehicles and approximately 100,000 drivers in New York City. Vendors appointed by them provide trip wise information via a Trip Sheet Data which is captured into a central pool and is made available publicly.

Monthwise (from Jan 2009 to June 2018) NYTaxi trip data is available as a CSV file for each of the three types of taxis: Green, Yellow and FHV. File sizes range from around 700Mb to 2.7Gb.

Due to file size and processing power constraints we are only working with one of the smaller files: Yellow Taxi - June 2018 data of approximately 750Mb size.

2.1 Data Description for Yellow Taxi

The data dictionary describes the fields (see References section). Each row has information such as trip distance, fare breakdown, number of passengers, pick up and drop off timestamps and locations, mode of payment, etc. The timestamps are in DD-MM-YYYY hh:mm:ss format and the location information is a unique number that indicates a general area. The range of the pickup locations is not explicitly given in the data dictionary but appears to range from 1 thru 265.

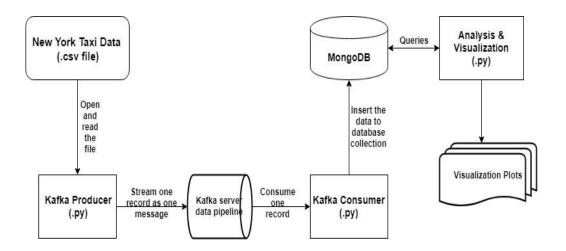
NOTE: For brevity the field Pick Up Datetime is referred to as PUdt from now. Similarly the Drop Off Datetime is called DOdt.

Data is well structured data with 17 columns and each trip is recorded as one row in the CSV file. The first row is a header with columns names and the second row contains only commas. Actual data starts from the third row and has the following fields for each trip: VendorID, PUdt, DOdt, number of Passengers, Distance covered, Rate Code, whether trip info was Stored and Forwarded, PU location, DO location, Payment Method, Fare breakdown (across multiple fields with grand total amount). Total rows in file (including the first two rows) = 8,713,832

Analysis of the file showed that a few rows (around 500) have PUdt of May-2018 or even of the year 2009 and 2010.

3 - Pipeline Structure and Overview

3.1 Data Ingestion, Storage and Visualization overview



Data Ingestion:

The data is taken from a static data source i.e. CSV file and sent into the Kafka pipeline. Since the data in the CSV is for the whole month of June, not all the data is used for analysis. Only the first 5 days of June data is used for data streaming. After opening this file each row is read and send by the producer to the kafka pipeline. To stream data only from the PUdt of June 2018, a check on the PUdt is applied by specifying necessary start and end date parameters and comparing with those bounds before sending message to Kafka.

One could have implemented the project by treating the data as a static source CSV file that is downloaded from the NYT website and directly processed into NoSQL DB. But we are implementing a Kafka pipeline from a learning outcome perspective.

In our implementation, the Kafka Producer is a python script that sends the messages. A second python script (Kafka Consumer in the diagram above) reads all the messages from Kafka.

Data Storage:

Kafka Consumer python script consumes the data from the Kafka topic and has been tested running it as a Single instance and also running five instances in parallel (as the topic was created with 5 partitions). After inspecting the PUdt from the message to ensure it falls within the a June 2018 date, the entire field values are extracted from the message and populated into a JSON format to write to the Mongo database collection.

Data Visualization:

Queries to the Mongo database are issued to extract information that can then be visualised via suitable plots. A trip duration field is derived by finding the difference between the PUdt and DOdt fields available in the trip data.

3.2 Kafka Producer

Kafka Producer is used to publish stream CSV's row wise contents to a Kafka topic which was created with 5 partitions. To avoid laptop crash with memory issues, the processing is done by reading one row at a time and sending it to as a message. Two values for the upper and lower boundaries of the PUdt are hardcoded in the producer program and are to be specified before running. In our project the upper bound is "2018-07-01 00:00:00" and the lower bound is "2018-06-01 00:00:00" to exclude any rows with non-June data. Thus only those rows with a PUdt within June will be sent to Kafka. This prevented around 500 rows from being sent in our case. Note we want to actually process only the first 28 days data but are purposely sending data spanning the next 2 days also.

```
boundLowerPUDatetime = '2018-06-01 00:00:00' # the pickup datetime from csv to be greater or equal to this boundUpperPUDatetime = '2018-07-01 00:00:00' # the pickup datetime from csv to be lower than this
with open(fileLocation, "r") as csv_file:
     csv reader = csv.reader(csv file, delimiter=".")
     for row in csv_reader:
          rowsReadcount = rowsReadcount + 1
          if rowsReadcount % 500000 == 0:
               print(f'Processing csv row number {rowsReadcount}')
          if rowsReadcount == (maxRows2Read + 1):
              print('Reached rows to read limit set by user')
print('Reached limit for first 24 hours and exiting last entry should have PickUp time of 01-06-2018 23:43:00')
               row_tpep_pickup_datetime = row[1]
          except:
               print(f'Skipped row as Error during PU date assignment for row={rowsReadcount}')
               continue
         print(f'row_tpep_pickup_datetime={row_tpep_pickup_datetime}')
if (row_tpep_pickup_datetime < boundUpperPUDatetime and row_tpep_pickup_datetime >= boundLowerPUDatetime):
    joinedRow = ','.join(row)
    producer.send(topicName, joinedRow.encode('utf-8'))
               countSent2Producer = countSent2Producer + 1
               if countSent2Producer % 500000 == 0:
          print(f'Row {rowsReadcount} not sent to producer, row PUDatetime={row_tpep_pickup_datetime} and outside bounds')
               boundNotMatchRowsCount = boundNotMatchRowsCount + 1
```

Example of the output displayed after the producer runs. It took about 80 minutes to run and sent almost the entire 8.71 million rows to Kafka while leaving out the 500 odd rows with non-June PUdt.

```
StartTime is: Wed Jan 9 23:08:02 2019
Skipped row as Error during PU date assignment for row=2
Processing csv row number 100000 at Wed Jan 9 23:08:25 2019
Processing csv row number 200000 at Wed Jan 9 23:08:40 2019
Processing csv row number 300000 at Wed Jan 9 23:09:01 2019
```

```
Sent 8500439 row as the 8500000 th message to Kafka
Processing csv row number 8600000 at Thu Jan 10 00:25:43 2019
Processing csv row number 8700000 at Thu Jan 10 00:26:45 2019

Processed 8713832 rows from csv
Sent 8713307 messages to Kafka
NOT SENT 524 rows as OB

EndTime is: Thu Jan 10 00:26:53 2019
```

3.3 Kafka Consumer

Salient features of the consumer implementation:

a) Use of Group name: allows running of multiple instances of the consumer program in parallel and speeds up processing and writing to MongoDb. Topic had been created with 5 partitions to support up to 5 such above instances. Below are snapshots from command prompt queries to Kafka server about number of messages in topic and the offsets for the individual consumers.

```
19 consumer = KafkaConsumer(
20 bootstrap_servers=['localhost:9092'],
21 auto_offset_reset='earliest',
22 # auto_offset_reset='latest', # default is latest
23 enable_auto_commit=True,
24 auto_commit_interval_ms=2000,
25 group_id='SingleRunning1')
```

Multi Instance Consumer Run:

Topic was created, producer was started and after about 10 seconds time we started FIVE instances of the consumer program in parallel with group name "MultipleRunning30-1".

```
C:\Everything\Kafka2.1.0-Scala2.12\bin\windows>kafka-topics.bat --create --zookeeper localhost:2181 --replication-factor 1 --partitions 5 --topic TestNYTJune30days Created topic "TestNYTJune30days".

C:\Everything\Kafka2.1.0-Scala2.12\bin\windows>kafka-run-class.bat kafka.tools.GetOffsetShell --broker-list localhost:9092 --topic TestNYTJune30days --time -1
TestNYTJune30days:1:0
TestNYTJune30days:1:0
TestNYTJune30days:1:0
TestNYTJune30days:3:0
TestNYTJune30days:1:0
TestNYTJune30da
```

At certain times, Kafka Broker did not use all the 5 instances and rebalanced to assign only 3 instances to the 5 partitions. See the transition below.

Consumer run has almost ended now with only two consumer instances still consuming.

Single Instance Consumer Run:

Now producer program has already run, we now again ran only ONE consumer with group name "SingleRunning30-1".

Here we can clearly see the single consumer slowly reading messages from each partition. In the first snapshot below, it has not even started consuming from some of the partitions as yet.

After around 115 mins of starting it consumes all the messages

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(7	mnarison c	nt execultion	i fime to	or the	SINGLE	consumer v/s	mulfi	consumer (~ 1	minc.
\sim	miparison c	n caccuuoi		or urc	3111210	Consumer v/s	munu	Consumo (J	i uns.

# of consumers in parallel	Runtime	Remarks
5	82 mins	Same computer (hardware Win10 with 8Gb ram). Producer and Multiple Consumers running with group
1	115 mins	name Multiple Consumers running with group name MultipleRunning30-1 at same time. At times, son consumers have already processed messages in the partition and are idle. Single instance consumer run after Producer ended already. So it ran without any downtime unlike some consumers in the multi-instance scenario. Group name SingleRunning30-1 Approx. 8.7 million messages consumed.

b) Even though the time period decided for analysis is only 28 days starting midnight of 01.06.2018 to midnight of 29.06.2018, we are reading messages outside this timeframe from the Kafka pipeline. Messages with PUdt within first 28 days are stored in one collection#1 and all (for 2 days in this case) are routed to another collection#2 in the same database.

```
boundLowerPUDatetime1 = '2018-06-01 00:00:00' # the pickup datetime from csv to be greater or equal to this boundUpperPUDatetime1 = '2018-06-29 00:00:00' # the pickup datetime from csv to be lower than this boundLowerPUDatetime2 = '2018-06-29 00:00:00' # the pickup datetime from csv to be greater or equal to this boundUpperPUDatetime2 = '2018-07-01 00:00:00' # the pickup datetime from csv to be lower than this '"total_amount": ' + str(msgAsList[16]) + '}' #print(f'Msg {msgsReadCount} - JSON built as=\n{NYYNewRowJsonBuiltUpAsString}')
         if \ ( \ str(msgAsList[1]) \ < \ boundUpperPUDatetime1 \ and \ str(msgAsList[1]) \ >= \ boundLowerPUDatetime1 \ ) : 
                    collection1.insert_one(loads(NYTNewRowJsonBuiltUpAsString))
                    \textit{\#print}(f"\textit{Collection 1 -- NO ERROR for \{\textit{msgsReadCount}\}\ th\ \textit{message insert"})}\ countDocsWritten1 = countDocsWritten1 + 1
                    if countDocsWritten1 % 200000 == 0:
                          print(f"Collection 1 - write SUCCESS - {msgsReadCount} th message as {countDocsWritten1} th insert at ", datet
                    if countDocsWritten1 % 500000 == 0:
                          print(f'Msg \ \{msgsReadCount\} \ - \ JSON \ built \ as=\n\{NYTNewRowJsonBuiltUpAsString\}')
              except Exception as e:
       print(f'Collection 1 ERROR Insert :: {msgsReadCount} th message\nError:: ', type(e), e)
elif ( str(msgAsList[1]) < boundUpperPUDatetime2 and str(msgAsList[1]) >= boundLowerPUDatetime2 ):
                    collection2.insert one(loads(NYTNewRowJsonBuiltUpAsString))
                    \#print(f"Collection 2 -- NO \ ERROR \ for \ \{msgsReadCount\} \ th \ message \ insert") \\ countDocsWritten2 = countDocsWritten2 + 1
                    if countDocsWritten2 % 200000 =
                    print(f"Collection 2 - write SUCCESS - {msgsReadCount} th message as {countDocsWritten2} th insert at ", datet if countDocsWritten2 % 500000 == 0:
                          print(f'Msg {msgsReadCount} - JSON built as=\n{NYTNewRowJsonBuiltUpAsString}')
              except Exception as e:
                    print(f'Collection 2 ERROR Insert :: {msgsReadCount} th message\nError:: ', type(e), e)
 else:
       print(f"{msgsReadCount} th message NOT having 16 commas so IGNORED MESSAGE")
```

c) Json is explicitly built in the consumer program itself. We cannot assume that the first message any instance of the consumer will access the header row from the CSV file. This could be done in the following way there are limited number of field.

3.4 Storage for Permanent Repository

MongoDb is being used for permanent storage. Allows for storing any changes in the data format as and when it occurs without affecting earlier entries. Also, no suitable unique key could be decided with certainty using the fields that are received from the CSV file. Therefore using a SQL DB is a challenge and we decided to implement using NoSQL MongoDb.

```
> odb.TestNYTJune30daysCol2Jun01to28.count()
8155479
> db.TestNYTJune30daysCol2Jun29to30.count()
557828
>
```

Example of an entry in the database:

```
db.TestNYTJune30daysCol2Jun01to28.find().skip(2140345).limit(1).pretty()

{
    "_id" : ObjectId("5c36b29c7fd09d108c12f0d9"),
    "VendorID" : 1,
    "tpep_pickup_datetime" : "2018-06-08 10:57:38",
    "passenger_count" : 1,
    "trip_distance" : 5.9,
    "RatecodeID" : 1,
    "store_and_fwd_flag" : "N",
    "PULocationID" : 87,
    "DOLocationID" : 87,
    "DOLocationID" : 170,
    "payment_type" : 1,
    "fare_amount" : 23,
    "extra" : 0,
    "mta_tax" : 0.5,
    "tip_amount" : 4.75,
    "tolls_amount" : 4.75,
    "tolls_amount" : 28.55

}
```

4 - Analysis and Visualization

4.1 Analysis of the data from MongoDB

We decided to analyse the data by slicing it on a daily basis to cover 4 weeks = 28 days. Later we took just one 24 window of "from 2018.06.01 00:00:00 to less than 2018.06.02 00:00:00". store the information into two data structures to be used later for the visualisation if required.

First is a matrix with 28 rows and 16 columns. Each row holds the aggregated or computed values for that day. The columns are for the various aggregate values such as total trips, total passengers, number of trips paid for by different payment methods, total fares, etc. Calculated fields are average values per trip for fare, distance and passengers as well as for the average duration of the trip per day.

Snapshots of part of the console output from the data structures:

From the matrix:

Note: Due to extremely long query time run time we are only running those queries that we decided to actually proceed with for analysis and some of the matrix parameters remain unpopulated and initialised to 0.

```
Analysis data:

Total Trips per day:

Day1 = 328529.0000 -- Day2 = 308393.0000 -- Day3 = 265244.0000 -- Day4 = 279353.0000 -- Day5 = 298140.0000 -- Day6 = 315354.00
00 -- Day7 = 319315.0000 -- Day8 = 315660.0000 -- Day9 = 293934.0000 -- Day10 = 249740.0000 -- Day11 = 278488.0000 -- Day12 = 295377.0000 -- Day13 = 312651.0000 -- Day14 = 316168.0000 -- Day15 = 281883.0000 -- Day16 = 275862.0000 -- Day17 = 247840.0000
-- Day18 = 281485.00000 -- Day29 = 29528.0000 -- Day20 = 307880.0000 -- Day21 = 309690.00000 -- Day22 = 311352.0000 -- Day28 = 302796.0000
--

Total Passenger per day:

Day1 = 57899.0000 -- Day2 = 509665.0000 -- Day3 = 431153.0000 -- Day4 = 436819.0000 -- Day5 = 466506.0000 -- Day6 = 494194.00
00 -- Day7 = 499014.0000 -- Day2 = 509665.0000 -- Day9 = 485392.0000 -- Day10 = 408601.0000 -- Day11 = 436463.0000 -- Day12 = 463919.0000 -- Day13 = 491022.0000 -- Day14 = 497015.0000 -- Day15 = 438738.0000 -- Day16 = 453013.0000 -- Day17 = 411547.0000
-- Day18 = 448265.00000 -- Day24 = 402607.0000 -- Day25 = 425725.0000 -- Day26 = 455372.0000 -- Day27 = 469436.0000 -- Day28 = 479499.0000
-- Day18 = 1.5846 -- Day2 = 1.6526 -- Day3 = 1.6255 -- Day4 = 1.5637 -- Day5 = 1.5647 -- Day6 = 1.5671 -- Day7 = 1.5628 -- Day8 = 1.5896 -- Day9 = 1.6514 -- Day10 = 1.6361 -- Day11 = 1.5673 -- Day12 = 1.5786 -- Day13 = 1.5785 -- Day14 = 1.5784 -- Day22 = 1.65824 -- Day21 = 1.5528 -- Day16 = 1.5846 -- Day21 = 1.5528 -- Day16 = 1.5846 -- Day21 = 1.5563 -- Day16 = 1.5856 -- Day16 = 1.6361 -- Day17 = 1.6065 -- Day18 = 1.5896 -- Day29 = 1.6514 -- Day10 = 1.6361 -- Day11 = 1.5673 -- Day26 = 1.5866 -- Day27 = 1.5787 -- Day28 = 1.5836 --

Count of StoreFwd=VES per day:

Day1 = 0.0000 -- Day2 = 0.0000 -- Day3 = 0.0000 -- Day4 = 0.0000 -- Day12 = 0.0000 -- Day14 = 0.0000 -- Day2 = 0.0000 -- Day14 = 0.0000 -- Day16 = 0.0000 --
```

```
Total Fare Amount per day:
Day1 = 512313,7590 -- Day2 = 4713918,0300 -- Day3 = 4514625.0000 -- Day4 = 4711105.2000 -- Day5 = 4984462.5000 -- Day6 = 5270
349.5900 -- Day7 = 5493762.6200 -- Day8 = 5309576.8800 -- Day9 = 4563087.7700 -- Day10 = 4265889.4200 -- Day11 = 4698539.5000
-- Day12 = 4942538.4200 -- Day13 = 5258794.0100 -- Day14 = 5452836.0000 -- Day15 = 4714651.8100 -- Day16 = 4203697.6900 -- Day17 = 4979151.6500 -- Day18 = 4688624.2500 -- Day19 = 4986225.0700 -- Day20 = 5261322.2100 -- Day21 = 5456459.9200 -- Day22 = 5 199650.6800 -- Day28 = 5152645.4900 --

Average Fare/Trip per day:
Day1 = 16.6073 -- Day2 = 15.2854 -- Day3 = 17.0206 -- Day4 = 16.8643 -- Day5 = 16.7185 -- Day6 = 16.7125 -- Day7 = 17.2048 --
Day8 = 16.8206 -- Day9 = 15.5242 -- Day10 = 17.0813 -- Day11 = 16.8716 -- Day12 = 16.7330 -- Day13 = 16.8200 -- Day14 = 17.0813 -- Day17 = 16.4838 -- Day18 = 16.8207 -- Day22 = 17.0839 -- Day12 = 17.6839 -- Day12 = 17.6845 -- Day22 = 16.6997 -- Day23 = 15.4825 -- Day24 = 16.9870 -- Day25 = 17.1758 -- Day26 = 16.5100 -- Day27 = 16.8176 -- Day28 = 17.0169 --

Total Distance per day:

Day1 = 929332.0200 -- Day2 = 864685.7100 -- Day3 = 871336.2100 -- Day4 = 864082.7100 -- Day5 = 862439.5600 -- Day11 = 86728.8938.000 -- Day13 = 84533.0400 -- Day14 = 494961.7000 -- Day4 = 864082.7100 -- Day2 = 871754.2100 -- Day2 = 871754.2100 -- Day28 = 873953.0400 -- Day12 = 867238.9300 -- Day13 = 894533.0400 -- Day14 = 949691.7000 -- Day15 = 879913.2300 -- Day12 = 871754.2100 -- Day28 = 873953.1900 --
Day18 = 854696.6700 -- Day19 = 867371.8100 -- Day26 = 845639.8400 -- Day17 = 871756.000 -- Day28 = 873963.1900 --
Day18 = 854696.6700 -- Day19 = 837371.8100 -- Day26 = 845639.8400 -- Day17 = 871754.2100 -- Day28 = 873963.1900 --
Day18 = 836696.6700 -- Day19 = 3.3791 -- Day11 = 3.1132 -- Day12 = 2.9360 -- Day12 = 871754.2100 -- Day28 = 873963.1900 --
Day18 = 836696.6700 -- Day29 = 2.8938 -- Day39 = 3.2850 -- Day49 = 3.0932 -- Day20 = 2.8914 -- Day20 = 2.9710 -- Day21 = 2.9933 -- Day20 = 2.8936 -- Day22 = 2.8936 -- Day22 = 2
```

The second data structure is a list. It can accommodate computed values for the top 5 maximum number of trips per hour starting from a certain PU (Pick-up) location, ending at a certain DO (Drop-Off) location. However for the combination of unique PU to DO location are captured into it holds the top 10 routes and their counts. Snapshot of the list contents is below. As we decided to focus only on the combination route and ignored the other two, one sees certain elements in the list are left unpopulated and initialised to their default values that were hardcoded the program.

The console displays the full information for each of the 28 days.

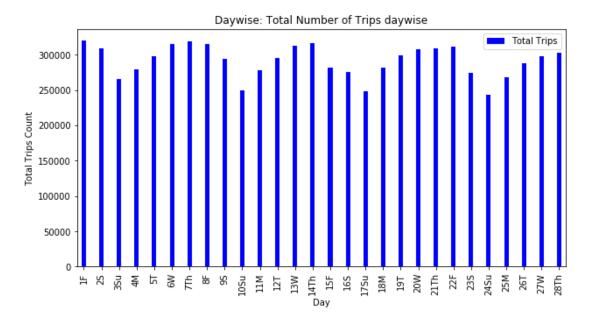
```
Day 1
D1 -- 2018-06-01 00:00 -- 2018-06-02 00:00:00
D1 -- 2018-06-01 00:00:00 -- 2018-06-02 00:00:00
D2 ("TopPULoc1", 'PULoc1-UNFILLED', 0], ['TopPULoc2', 'PULoc2-UNFILLED', 0], ['TopPULoc3', 'PULoc3-UNFILLED', 0], ['TopPULoc4', 'PULoc4-UNFILLED', 0], ['TopPULoc5', 'PULoc3-UNFILLED', 0], ['TopPULoc4', 'DULoc4-UNFILLED', 0], ['TopPULoc5', 'PULoc3-UNFILLED', 0], ['TopPULoc4', 'DULoc4-UNFILLED', 0], ['TopPULoc5', 'DULoc5-UNFILLED', 0]]
[['TopPUDOCombo1', '264 TO 264', 3276], ['TopPUDOCombo2', '237 TO 236', 2090], ['TopPUDOCombo3', '236 TO 236', 1878], ['TopPUDOCOmbo7', '236 TO 237', 1764], ['TopPUDOCombo7', '237 TO 237', 1471], ['TopPUDOCombo6', '237 TO 236', 2481], ['TopPUDOCombo7', '239 TO 142', 908], ['TopPUDOCombo8', '237 TO 162', 859], ['TopPUDOCombo9', '238 TO 239', 814], ['TopPUDOCombo7', '239 TO 142', 908], ['TopPUDOCombo8', '237 TO 162', 859], ['TopPUDOCombo9', '238 TO 239', 814], ['TopPUDOCombo10', '141 TO 23 de', 814]]

Day 2
D2 -- 2018-06-02 00:00:00 -- 2018-06-03 00:00:00
[['TopPULoc1', 'PULoc1-UNFILLED', 0], ['TopPULoc2', 'PULoc2-UNFILLED', 0], ['TopPULoc3', 'PULoc3-UNFILLED', 0], ['TopPULoc4', 'PULoc4-UNFILLED', 0], ['TopPULoc3', 'PULoc3-UNFILLED', 0], ['TopPULoc4', 'PULoc4-UNFILLED', 0], ['TopPULoc4', 'PULoc4-UNFILLED', 0], ['TopPUDOCombo7', '236 TO 236', 1415], ['TopPUDOCombo7', '236 TO 236', 1415], ['TopPUDOCombo6', '239 TO 142', 1038], ['TopPUDOCombo7', '236 TO 236', 1416], ['TopPUDOCombo7', '237', 1081], ['TopPUDOCombo6', '239 TO 142', 1038], ['TopPUDOCombo7', '79 TO 79', 906], ['TopPUDOCombo8', '239 TO 238', 828], ['TopPUDOCombo6', '239 TO 142', 1038], ['TopPUDOCombo7', '236 TO 236', 1416], ['TopPUDOCombo7', '237', 1081], ['TopPUDOCombo7', '236 TO 236', 1416], ['TopPUDOCombo7', '237 TO 236', 1415], ['TopPUDOCombo7', '236 TO 236', 1416], ['TopPUDOCombo7', '237 TO 236', 1417, ['TopPUDOCombo7', '236 TO 236', 1416], ['TopPUDOCombo7', '237 TO 236', 1417, ['TopPUDOCombo7', '236 TO 236', 1416], ['TopPUDOCombo7', '237 TO 236', 1417], ['TopPUDOCombo7', '236 TO 237', 1858], ['TopPUDOCombo7', '237 TO 23
```

4.2 Visualization

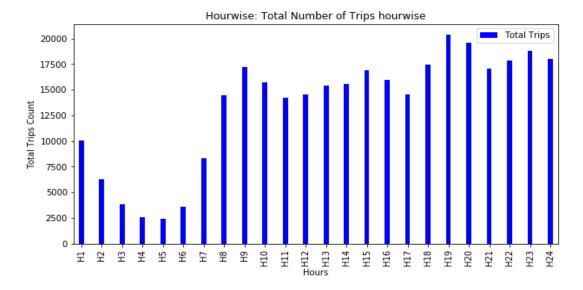
Plot 1: Total Number of trips per day from 01.06 to 28.06

- Total trips vary from around 265k to 315k
- Maximum demand on Thursdays and Fridays, lowest on Sunday



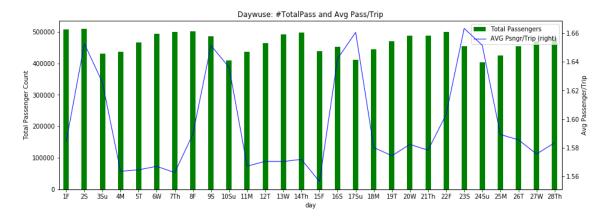
Plot 2: Total Number of trips per hour on 01.06.2018 (Friday)

- H2 to H6: Low number of trips during dead of night till H5 and then very slow turnaround towards rising numbers seen for H7 between 0500 to 0600
- H8 to H18: Number of trips almost steady around 16000 per hour
- H19 to H24: Number of trips rises to 20k+ and remains higher than before H18 probably due to Friday night and late turn in by NY population.



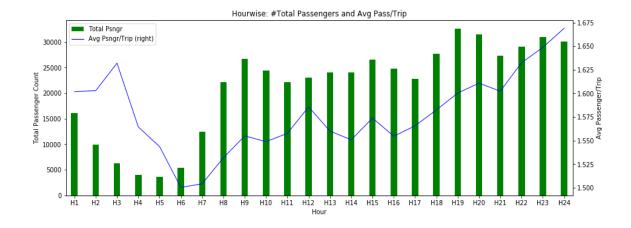
Plot 3: Daily variation of Total passengers v/s average number of passengers/trip (28 days)

- Average Passengers per Trip low from Monday to Thursday and higher on weekends
- Possibly single ride tendency increases on weekends
- Total number of passengers taking taxis follows the total trips trend cycle in general



Plot 4: Total passengers per hour and the average number of passengers per trip

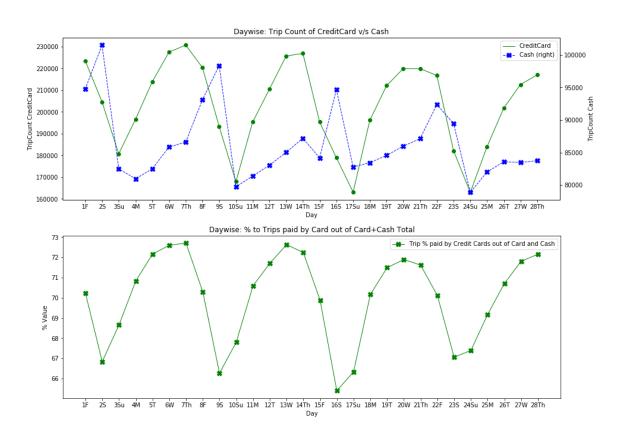
- H3 to H5: Total passengers dropped by 40% (6293 to 3677), (total number of trips fell by 40%), Avg Psng/Trip fell 5% (1.63 to 1.54) => during this time period, the tendency for multi passenger trips is higher
- H12 to H14: Passenger total remained steady or increased very slightly, but the avg Psng/Trip fell by about 3% => single ride tendency increased.



Plot 5: Daily variation (28 days): Number of trips paid for by Credit Card v/s Cash Plot 6: Daily variation (28 days): % to Trips paid by Card out of Card+Cash

Total

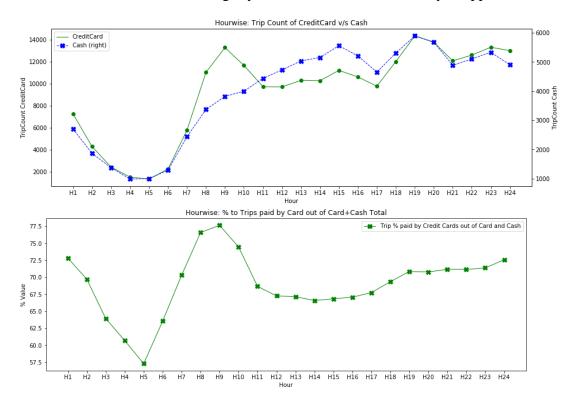
- Share of credit card payments as against cash is maximum from Tuesdays to Thursdays and Lowest on weekends
- 3 out 4 Saturdays rank highest in the week for number of trips paid for with cash during a week



Plot 7: Hour wise variation on 01.06: Number of trips paid for by Credit Card v/s Cash

Plot 8: Hour wise variation on 01.06: % to Trips paid by Card out of Card+Cash Total

- H5 to H9: Ratio of Card payment against trips paid for by only Cash i.e Card payment continued to increase steadily from approx 60% to 80%
- H9 to H17: The overall use dropped to about 65% by H12 and remained steady till H17
- H17 to H24: Increased slightly till H19 and remained steady at approx. 72%

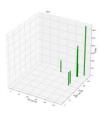


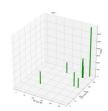
Plot 9: Daily Top 10 demand routes 28 days - PU to DO Location

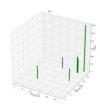
- PU Loc 264 to DO Loc 264 appears within top 10 each day and it has the highest demand daily with over 3000 trips per day
- Trips to and fro for combinations of LocID's 236 and 237 feature consistently in the next top 4 routes by demand
- Except on Saturday's and Sunday's, all the top 10 locations ID's of PU to DO combo are concentrated around the 200 locations

There was a GIF which showed the daily variation by cycling through the plots for 28 DAYS data. As the PDF report will not support the GIF attached below are three sample images. Please open the link for the document on google drive to see the running GIF file. Link to google drive document:

 $\frac{https://docs.google.com/document/d/10vX5QoYbKUnLSj1bU1SzATITtqGUT6L}{ednKgAYoKKeo/edit?usp=sharing}$







Plot 10: Hourly Top 5 in demand routes on 01.06 - PU to DO Location

- H1 to H22: The top 5 PU to DO locations are almost the same throughout
- Location 264: PU Loc 264 to DO Loc 264 appears in 23 out of the 24 hours within top 5 list. Also, for 17 of these hours it has the highest number of trips.
- Variability in trip count for top most PU-DO combination is from low 20's (H4 to H5) and peaks around 225 range (H22 to H24)

0000-0100 hrs

PULoc 48 to DOLoc 68 = 26 trips PULoc 79 to DOLoc 79 = 31 trips PULoc 249 to DOLoc 79 = 27 trips PULoc 79 to DOLoc 107 = 25 trips PULoc 264 to DOLoc 264 = 110 trips

0100-0200 hrs

PULOC 48 to DOLOC 48 = 23 trips PULOC 79 to DOLOC 79 = 27 trips PULOC 114 to DOLOC 79 = 22 trips PULOC 148 to DOLOC 79 = 26 trips PULOC 264 to DOLOC 264 = 69 trips

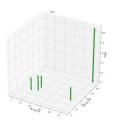
2300-0000

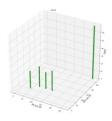
PULOC 48 to DOLOC 48 = 54 trips PULOC 48 to DOLOC 68 = 60 trips PULOC 79 to DOLOC 79 = 50 trips PULOC 79 to DOLOC 148 = 52 trips PULOC 264 to DOLOC 264 = 228 trips

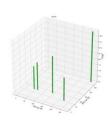
There was a GIF which showed the daily variation by cycling through the plots for 24 HOURS data. As the PDF report will not support the GIF attached below are three sample images. Please open the link for the document on google drive to see the running GIF file.

Link to google drive document:

https://docs.google.com/document/d/10vX5QoYbKUnLSj1bU1SzATITtqGUT6LednKgAYoKKeo/edit?usp=sharing

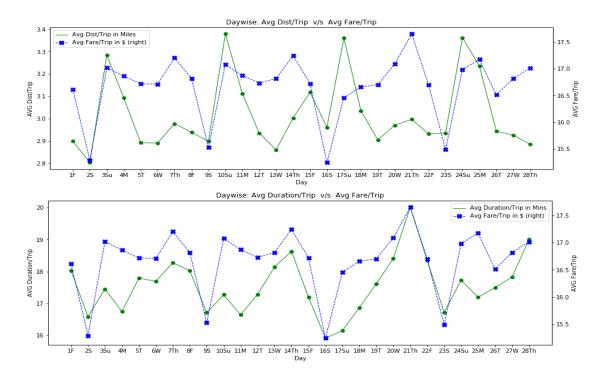






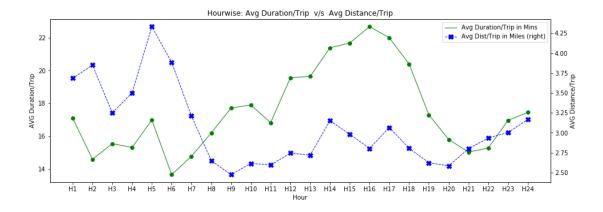
Plots 11, 12: Daily variation of Fare/Trip - the effect of Duration/Trip and Distance/Trip for 28 days of June

- Avg Fare/trip evinces clear pattern in first two weeks of June with troughs on Saturday, peaks on Sunday and Thursday.
- Avg Distance is consistently high on Sundays and that impacts the Avg fare making it high even though the Avg Duration is on lower side.
- On Thursday the high Avg Duration has same effect and low Avg Distance has limited impact
- On 17th as duration remained low the regular peak on Sunday was subdued even with high Avg Dist, the 21st Thur the fare is really high as duration goes higher than normal



Plots 13: Hourly variation of Average Duration/Trip and Distance/Trip on 01.06

- During early hours (H2 to H7) duration per trip remains low while the distance per trip remains high supports low congestion during dead of night.
- H6 to H17, congestion picks up as distance per trip falls to a low steady value but duration per trip continues to increase.
- H17 onwards duration keeps falling as distance falls again.



5 - Challenges and Learnings

a) The CSV file had over 8 million rows and opening it in Excel truncated and showed only around first one million rows. Visual inspection indicated that the rows towards the start of the file were for 01.06.2018 and spanned row #3 (with PUdt as "01-06-2018 00:15:40") till probably around row #325000. But the data was not sorted on the PUdt and it would not be fool proof to assume a 01.06.2018 date data would not appear in the truncated portion of the file.

Sorting on the PUdt showed there were records with dates of May 2018 and a few stray records from 2008 and 2009 too.

	A1 ▼	f_x	tpep_pickup_c	datetime
1	А		С	
1	tpep_pickup_datetir	tpep_dropoff	_datetime	
2	31-12-2008 13:51	3	1-12-2008 14:21	
3	01-01-2009 17:22	0	1-01-2009 18:05	
4	31-05-2018 06:08	3	1-05-2018 06:18	
5	31-05-2018 06:33	3	1-05-2018 06:35	
6	31-05-2018 06:40	3	1-05-2018 06:45	

Therefore, we had to implement a program based check in the producer python script to read the whole CSV file but to only process rows who's PUdt falls within our predefined boundary conditions (hardcoded in the program). Only these rows will be sent to the Kafka pipeline.

- **b)** We took time to understand the parameters of Kafka consumer such as effective use of group_id, auto_offset_reset, consumer_timeout_ms and enable_auto_commit. Not been able to use either the synchronous or an asynchronous type commit issued explicitly from the consumer. Therefore, we are relying purely on auto-commit being enabled and reducing the default auto_commit_interval_ms from 5 seconds to 2 seconds.
- c) Mongo query building is arcane, takes effort and care especially those involving aggregate queries with sections for \$match, \$project, \$group, \$limit and \$sort. E.g. the one to "find top 5 COMBINATION OF Pick Up TO Drop Off locations by count".

There is the other query below to find the duration of the trip that involves first converting the the PUdt and DOdt fields from string to ISO Date format, then finding the different, dividing to convert to minutes and then grouping using average.

```
pipeline=pipeline = [{"$match": {"tpep_pickup_datetime": {"$gte": "2018-06-01
00:00:01",
                    "2018-06-01
            "$lt":
                                  00:00:02"}}},
                                                 {"$project":
"TripDurationInMins": {
                       "$divide": [ {"$subtract":
                                                [ {
                                                      "$dateFromString":
{"dateString": "$tpep_dropoff_datetime"} } , { "$dateFromString": {"dateString":
"AvgTripDurationInMins": {"$avg": "$TripDurationInMins"} } }]
pipeline[0]['$match']['tpep_pickup_datetime']['$gte'] = timeBoundLower
pipeline[0]['$match']['tpep_pickup_datetime']['$lt'] = timeBoundUpper
cursorAvgDurationPerTrip = collection.aggregate(pipeline)
```

d) During testing it was found that if the trip distance was 0 then it was passed in by our consumer as .00 and created an error while building the JSON for MongoDb write. So special code was inserted to handle this situation.

```
msgAsList = msgAsString.split(",")

trip_distanceAsString = str(msgAsList[4])

if trip_distanceAsString[0:1] == '.': # a 0 value comes as .00 so checking and making as 0.00

trip_distanceAsString = '0' + trip_distanceAsString
```

e) An attempt was made to analyse the data streamed in kafka using spark. There are some hurdles for integrating the kafka server and spark. Even after spark installations were completed there were issues with the spark initializations.

We wanted to show a real time analysis to display:

- The trip with highest fare streamed thus far
- The trip with highest distance.
- The running count of the trips originating with a certain pick up location (PU) id eg. Location id 264 has 80 trips so far.

Since, we were unable to start Spark, we could not perform the above mentioned analysis.

6 - Bibliography

1) NYC Taxi related site

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2) Data dictionary for Yellow Taxi file

http://www.nyc.gov/html/tlc/downloads/pdf/data_dictionary_trip_records_yellow.pdf

3) Kafka and Zookeeper Related Sites

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https://docs.mongodb.com/manual/reference/operator/aggregation/dateFromString/

https://stackoverflow.com/questions/41564510/convert-string-date-to-timestamp-in-mongodb

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https://www.geeksforgeeks.org/python-string-split/

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client.MongoClient

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streaming-using-python-9cd0922fa904

https://spark.apache.org/downloads.html

https://www.youtube.com/watch?v=18jMvfOU3vQ

http://spark.apache.org/docs/latest/building-spark.html#setting-up-mavens-memory-usage

7) Miscellaneous

https://gifmaker.me/