



INFORMATICS INSTITUTE OF TECHNOLOGY In Collaboration With ROBERT GORDON UNIVERSITY ABERDEEN

MSc. in Big Data Analytics 2019/2020

By

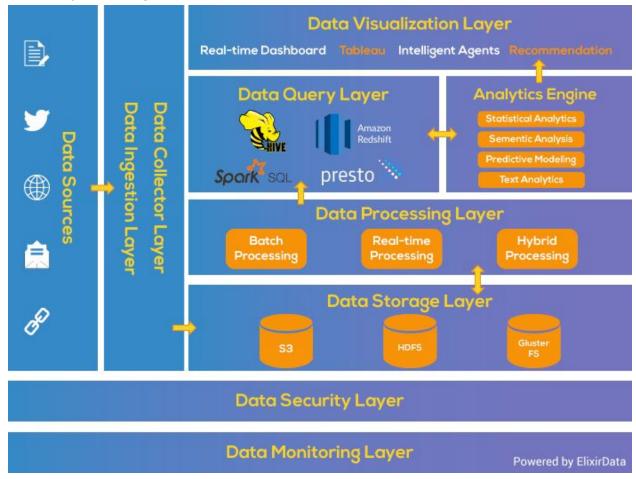
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CMM705

Web Dashboard, Scripts, and other files are in the following GitHub Repository:

https://github.com/SanjayaDeSilva/bdp_coursework_2019004

Q1)Deployment Diagram



When we consider Big Data, normally it will be either Batch or Stream Processing Systems. Above architecture has 6 layers to ensure the flow of data.

1. Data Ingestion Layer.

This is the 1st step where data coming from various sources for the journey.

2. Data collector Layer.

This layer is where components are decoupled and start the pipeline for analytics.

3. Data Storage Layer.

Where data store in various formats effectively for the processing.

4. Data Processing Layer.

Real Time, Hybrid, Batch Processing happens in this layer.

5. Data Query Layer.

Here happens analytics processing(spark, hive, ...). Focus here is gathering data in order To get help from them in the upcoming years.

6. Data Visualization Layer.

This is where present the analyzed data to the end user using dashboards or other methods.

Q2) Analysis for Singapore Airbnb

Given data-set has imported to the data-lake as an external table. The Following screens show the formation of the external table in data-lake.

```
sanjaya@sanjaya:-/Dev/MSc/BDPS sudo docker run -p 8088:8088 -p 50070:50070 -v /home/sanjaya/Dev/MSc/BDP:/resources --name hadoop-hive-pig -d suhothayan/hadoop-hive-pig:2.7.1
42edzedb75oc0di6a2ebb5de10046fd24011bbd2992c165a03964ae040d150f
sanjaya@sanjaya:-/Dev/MSc/BDPS sudo docker exec -tt hadoop-hive-pig bash
bash-4.1# hdfs dfs -nkdir /externaltablenew
20/01/10 01:50:09 WARN util.NativecodeLoader: Unable to load native-hadoop library for your platform... using builtin-java classes where applicable
mkdr: Cannot create directory /externaltablenew. Name node is in safe mode.
bash-4.1# hdfs dfsadmin -safemode leave
20/01/10 01:57:19 WARN util.NativecodeLoader: Unable to load native-hadoop library for your platform... using builtin-java classes where applicable

Safe mode is OFF
bash-4.1# hdfs dfs -mkdir /externaltablenew
20/01/10 01:57:27 WARN util.NativecodeLoader: Unable to load native-hadoop library for your platform... using builtin-java classes where applicable
bash-4.1# hdfs dfs -put listings.css / externaltablenew
20/01/10 01:57:27 WARN util.NativecodeLoader: Unable to load native-hadoop library for your platform... using builtin-java classes where applicable
put: 'listings.csv': No such file or directory
bash-4.1# lofts offs -put listings.css /externaltablenew
20/01/10 01:57:20 WARN util.NativecodeLoader: Unable to load native-hadoop library for your platform... using builtin-java classes where applicable
bih boot derby.log dev etc home lib lib64 media metastore_db mnt opt proc resources root sbin selinux srv sys tmp usr var
bash-4.1# lof resources/
bash-4.1# lof resources/
bash-4.1# lof resources/
bash-4.1# hdfs dfs -put listings.csv /externaltablenew
20/01/10 02:00:09 WARN util.NativecodeLoader: Unable to load native-hadoop library for your platform... using builtin-java classes where applicable
```

2.1) Analyze the flowing using Hadoop Map Reduce

1. Total number of rentals that are available 365 days a year.

```
3. Include the contents that alle available 305 days a year.

20/41/2 88:30:10 MAN util.Nativecodeloader: Umable to load native-hadopo library for your platforn... using builtin-java classes where applicable 20/41/2 88:30:10 MAN util.Nativecodeloader: Umable to load native-hadopo library for your platforn... using builtin-java classes where applicable 20/41/2 88:30:11 Milo Importation processes in the content of the conten
```

2. Number of rentals per neighbourhood group

```
2. Number of rentals per neighbourhood_group

Dash-4.1# yarn jar booking-0.8.1-SNAPSHOT.jar com.example.map.TotalRentals listings.csv output/wordCountin
20/01/12 08:14:48 WARN utll.NativeCodeLoader: Unable to load native-hadoop library for your platform... using builtin-java classes where applicable
20/01/12 08:14:49 INFO clent.RMProxy: Connecting to ResourceManager at /0.0.0.0:8032
20/01/12 08:14:49 INFO input.FileInputFormat: Total input paths to process: 1
20/01/12 08:14:49 INFO mapreduce.JobSubmitter: number of splits:1
20/01/12 08:14:49 INFO mapreduce.JobSubmitter: Submitting tokens for job: job_1578830731805_0006
20/01/12 08:14:49 INFO inpl.YarnClientImpl: Submitted application application_1578830731805_0006
20/01/12 08:14:49 INFO mapreduce.Job: In url to track the job: http://35184648:8088/proxy/application_1578830731805_0006/
20/01/12 08:14:49 INFO mapreduce.Job: Numing job: job_1578830731805_0006
20/01/12 08:14:51 INFO mapreduce.Job: in plob in 578830731805_0006 running in uber mode: false
20/01/12 08:14:53 INFO mapreduce.Job: Dab job_1578830731805_0006 running in uber mode: false
20/01/12 08:14:57 INFO mapreduce.Job: Dab job_1578830731805_0006 completed successfully
20/01/12 08:14:57 INFO mapreduce.Job: Dab job_1578830731805_0006 completed successfully
20/01/12 08:14:57 INFO mapreduce.Job: Ounters: 35
File: Number of bytes written=115437
File: Number of bytes written=115437
File: Number of bytes written=164787
HDFS: Number of bytes written=0
HDFS: Number of read operations=0
HDFS: Number of read operations=0
HDFS: Number of large read operations=0
Launched map tasks=1
                                                                                                                                   nters

Launched map tasks=1

Data-Local map tasks=1

Total time spent by all maps in occupied slots (ms)=1833

Total time spent by all map tasks (ms)=1833

Total time spent by all map tasks (ms)=1833

Total vcore-seconds taken by all map tasks=1833

Total megabyte-seconds taken by all map tasks=1876992

Local Framework
                                                             Total megabyte-seconds taken by all map tasks
Map-Reduce Framework
Map input records=7922
Map output records=0
Input split bytes=112
Spilled Records=0
Failed Shuffles=0
Merged Map outputs=0
GC time elapsed (ms)=17
CPU time spent (ms)=650
Physical memory (bytes) snapshot=162451456
Virtual memory (bytes) snapshot=753610752
Total committed heap usage (bytes)=148897792
Region
                                                                 Region
Central Region=5350
East Region=455
North Region=168
North-East Region=295
West Region=453
File Input Format Counters
                                                                     Bytes Read=1164675
File Output Format Counters
                                                                                                                                   Bytes Written=0
```

```
Central Region
                 5350
East Region
                 455
North Region
                 168
North-East Region
                         295
                 453
West Region
```

2.2) Analyze the flowing using Hive or Pig

2.2)1. Average price of Private room rental by neighbourhood group.

```
bash-4.1# hive
Logging initialized using configuration in jar:file:/usr/local/apache-hive-1.2.2-bin/lib/hive-common-1.2.2.jar!/hive-log4j.properties
hive> select neighbourhood_group,avg(cast(price as float)) price_ from dbpdata where room_type='Private room' group by neighbourhood_group;
Query ID = root_20200110021728_c684147c-6581-4983-a113-8c3b4c7157a7
Total jobs = 1
 leaunching Job 1 out of 1
Number of reduce tasks not specified. Estimated from input data size: 1
In order to change the average load for a reducer (in bytes):
In order to change the average load for a reducer (in bytes):
set hive.exec.reducers.bytes.per.reducers-cumber>
In order to limit the maximum number of reducers:
set hive.exec.reducers.max=<number>
In order to set a constant number of reducers:
set mapreduce.job.reduces=<number>
Starting Job = job_1578639354845_0004, Tracking URL = http://42ed2e4b750c:8088/proxy/application_1578639354845_0004/
Kill Command = /usr/local/hadoop/bin/hadoop job -kill job_1578639354845_0004
Hadoop job information for Stage-1: number of mappers: 1; number of reducers: 1
 2020-01-10 02:17:35,103 Stage-1 map = 0%, reduce = 0%
2020-01-10 02:17:35,103 Stage-1 map = 100%, reduce = 0%, Cumulative CPU 1.25 sec
2020-01-10 02:17:44,424 Stage-1 map = 100%, reduce = 100%, Cumulative CPU 2.23 sec
MapReduce Total cumulative CPU time: 2 seconds 230 msec
 Ended Job = job_1578639354845_0004
MapReduce Jobs Launched:
 Stage-Stage-1: Map: 1 Reduce: 1 Cumulative CPU: 2.23 sec HDFS Read: 1175535 HDFS Write: 161 SUCCESS Total MapReduce CPU Time Spent: 2 seconds 230 msec
 Central Region 121.04909983633388
 East Region 121.28528528528528
North Region 79.7094017094017
 North-East Region 79.9531914893617
West Region 125.21913580246914
 West Region 125.21913580246914
Time taken: 16.589 seconds, Fetched: 5 row(s)
hive>
```

2.2)2. Top 10 neighbourhood based on Average price of Private room.

2.2)3. The 5 lowest price properties per each room_type.

i. Private room Type

ii. Shared Room Type

iii. Entire home/apt

2.3)

Analyze the flowing using Spark

2.3)1. Percentage of owners who rent more than one property.

```
%pyspark
#2.3 .
#1. Percentage of owners who rent more than one property.
from pyspark.sql import *

#DF as a SQL tem view
df.createOrReplaceTempView("listing_temp_tbl")
#df.show()
#Fetch the count of tot owners
owners = spark.sql("select host_id, host_name, COUNT(*) as Properties from listing_temp_tbl group by host_id, host_name Order by Properties DESC")
OwnersCount=owners.count()

# Getting the count of tot no of multiple property owners
ownersgtone = spark.sql("select host_id, host_name, COUNT(*) as Properties from listing_temp_tbl group by host_id, host_name HAVING Properties>1 Order by Properties DESC")
ownersgtone = spark.sql("select host_id, host_name, COUNT(*) as Properties from listing_temp_tbl group by host_id, host_name HAVING Properties>1 Order by Properties DESC")
ownersgtone = spark.sql("select host_id, host_name, COUNT(*) as Properties from listing_temp_tbl group by host_id, host_name HAVING Properties>1 Order by Properties DESC")
ownersgtone = spark.sql("select host_id, host_name, COUNT(*) as Properties from listing_temp_tbl group by host_id, host_name HAVING Properties>1 Order by Properties DESC")
ownersgtone = spark.sql("select host_id, host_name, COUNT(*) as Properties from listing_temp_tbl group by host_id, host_name HAVING Properties>1 Order by Properties DESC")
ownersgtone = spark.sql("select host_id, host_name, COUNT(*) as Properties from listing_temp_tbl group by host_id, host_name Order by Properties DESC")
ownersgtone = spark.sql("select host_id, host_name, COUNT(*) as Properties from listing_temp_tbl group by host_id, host_name Order by Properties DESC")
ownersgtone = spark.sql("select host_id, host_name, COUNT(*) as Properties from listing_temp_tbl group by host_id, host_name Order by Properties DESC")

***Percentage of owners who rent more than one property***
27.3163528977
```

2.3)2. Histogram of number of rentals reviewed over time (based on last_review) in mouth Granularity.

```
%pyspark
#2.3
#2. Histogram of number of rentals reviewed over time (based on last_review) in mouth granularity.
import pandas as pd
from pyspark.sql.functions import *
histogramdf = spark.sql("Select month(last_review)month ,count(*)as sum from listing_temp_tbl where month(last_review) is not null group by month order by month")
print(histogramdf.show())
 \label{linear_histogramdf} histogramdf pandas = histogramdf pandas () \\ histPlot = histogramdf pandas.plot.bar(x='month', y='sum', color='orange') \\
      1 241
      2 236
      3 235
      4 249
      5 334
      6 455
      7 983
      8 | 1822 |
      9 149
     10 | 125 |
     11 | 111 |
     12 | 201 |
<matplotlib.figure.Figure at 0x7fcd0c6dc8d0>
 1750
 1500
 1250
 1000
   750
   500
                                                                              9
Took 2 sec. Last updated by anonymous at January 10 2020, 4:47:36 PM.
```

2.3)3. Number of rentals that are available all 365 days of the year for each neighbourhood, that are in the neighbourhood which have top 5 average rental prices.



3. Performing Machine Learning on the Singapore Airbnb Data

Import required libraries

```
%pyspark
# 3.ML on the Singapore Airbnb Data
from pyspark.sql import SparkSession, Row, functions, types from pyspark.sql.functions import udf
import numpy as np
import pandas as pd
from pandas import DataFrame
from pyspark.ml.feature import HashingTF, IDF, Tokenizer, VectorAssembler, StringIndexer from pyspark.ml.evaluation import MulticlassClassificationEvaluator
from pyspark.mllib.regression import LabeledPoint
from pyspark.ml.classification import NaiveBayes
from pyspark.mllib.evaluation import MultilabelMetrics
from pyspark.mllib.linalg import Vectors
from pyspark.ml import Pipeline
from pyspark.ml.tuning import CrossValidator, ParamGridBuilder
from pyspark.mllib.evaluation import MulticlassMetrics, BinaryClassificationMetrics
from pyspark.rdd import RDD
from pyspark.sql.functions import col
from pyspark.sql.Tunctions import colimport pandas as pd import numpy as np from pyspark.sql import functions as F from pyspark.sql.functions import when from pyspark.sql import SparkSession from pyspark.ml.feature import VectorAssembler from pyspark.ml.classification import LogisticRegression from pyspark.mllib.evaluation import MulticlassMetrics
from pyspark.mllib.evaluation import MulticlassMetrics
from pyspark.sql import functions as F
from pyspark.sql.functions import lit
from datetime import date
from pyspark.sql.types import StructField
from pyspark.sql.types import StructType
from pyspark.sql.types import *
from pyspark.mllib.evaluation import MulticlassMetrics
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
from pyspark.mllib.evaluation import MultilabelMetrics
from pyspark.mllib.evaluation import MulticlassMetrics, BinaryClassificationMetrics
 from pyspark.rdd import RDD
```

Next, we have to do the preprocessing and make our training and testing data sets.

```
| SPANN JOB FORCHED | II | Set | Shade Proprocessing | Statistics of Indicates and wise a new destifuse | features-[16] [latitude, 'Indicates', 'Indicates, 'Indica
```

Created the feature vector from dataset and dividing them into training and testing data(70% for training and 30% for testing) after scaling data.

```
def vectAssembler(df,impFeatures):
     print("Vector assembler ")
assembler = VectorAssembler(inputCols=impFeatures,outputCol="features")
df_new=assembler.transform(df)
      print("vector assembling is done.")
 return df_new
impFeatures=['latitude','longitude']
impdf = df2_training.select(impFeatures).show()
# Create a feature vector column using latitude and longitude
 dtf=vectAssembler(df2_training,impFeatures)
 finalized_data = dtf.select('label_column', 'features')
 from pyspark.ml.feature import StandardScaler scaler = StandardScaler(inputCol='features', outputCol='scaledFeatures', withStd=True, withMean=True) scalerModel = scaler.fit(finalized_data)
 classiFinalData = scalerModel.transform(finalized_data)
 # Splitting data into training and test sets (30% for testing)
 (trainingData, testData) = classiFinalData.randomSplit([0.7, 0.3])
trainingData.show()
| 110110|100100100|
+-----
only showing top 20 rows
Vector assembler
vector assembling is done.
                      features| scaledFeatures|
|label_column|
            1|[1.24387,103.84246]|[-2.3040593559511...|
            1|[1.24526,103.83999]|[-2.2585108654236...|
            1|[1.24847,103.82389]|[-2.1533233441333...|
            1|[1.24853,103.82502]|[-2.1513572222400...|
             1|[1.24881,103.82364]|[-2.1421819867381...|
             1|[1.24918,103.82509]|[-2.1300575683962...|
             1|[1.24992,103.82441]|[-2.1058087317125...|
             1| [1.2504,103.82539]|[-2.0900797565663...|
             1|[1.25046,103.82529]|[-2.0881136346730...|
Took 1 sec. Last updated by anonymous at January 10 2020, 2:49:07 PM. (outdated)
```

After train and testing, get the predictions.

Model Evaluation

```
%pyspark
from pyspark.mllib.evaluation import MulticlassMetrics
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
from pyspark.mllib.evaluation import MulticlassClassificationEvaluator
from pyspark.mllib.evaluation import MulticlassMetrics
from pyspark.mllib.evaluation import MulticlassMetrics, BinaryClassificationMetrics
from pyspark.rdd import RDD

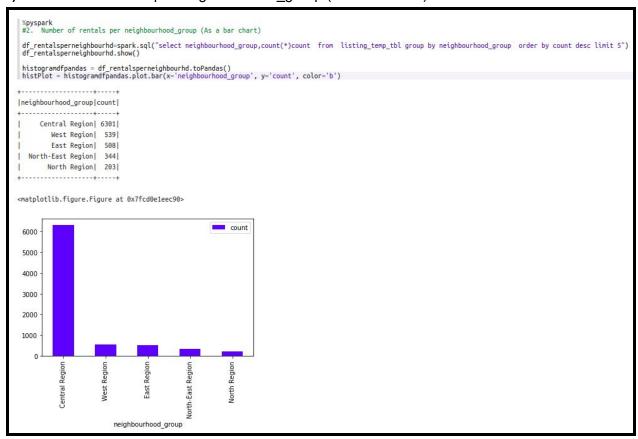
evaluatorRecall = MulticlassClassificationEvaluator(labelCol="label_column", predictionCol="prediction", metricName="weightedRecall")
evaluatorPrecision = MulticlassClassificationEvaluator(labelCol="label_column", predictionCol="prediction", metricName="weightedPrecision")
recall = evaluatorRecall.evaluate(predictions)
precision = evaluatorPrecision.evaluate(predictions)
print("Recall %s" % recall)
print("Precision %s" % precision)

Recall 0.981865284974
Precision 0.981982630764
```

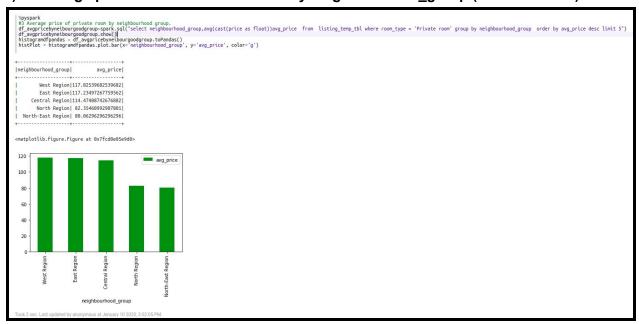
4). Presentation of the analysis for Singapore Airbnb Data

4)1. Total number of rentals that are available 365 days a year, and the total number of rentals.(As numbers)

4)2. Number of rentals per neighbourhood_group (As a bar chart)



4)3. Average price of Private room rental by neighbourhood_group (As a bar chart).



4)4. Top 10 neighbourhood based on Average price of Private room (As a table).



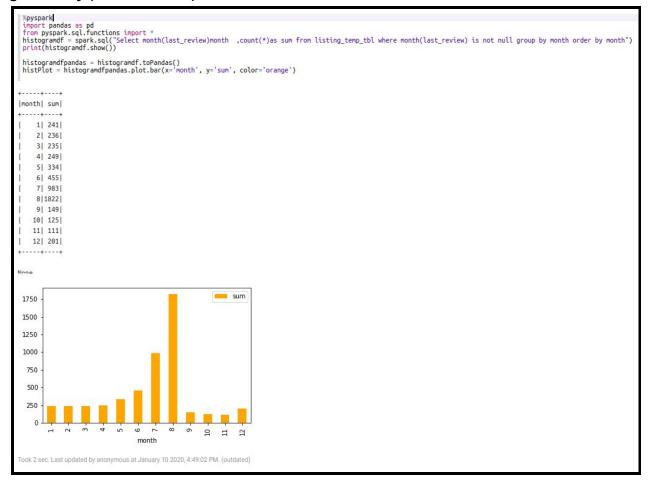
4)5. The 5 lowest price rentals per each room_type (As a table).

```
%pyspark
# 5 lowest price per each room type
df avgpricebyneibourhood-spark.sql("select neighbourhood_group, neighbourhood,price
from listing_temp_tbl where room_type = 'Private room' order by price asc limit 5")
df avgpricebyneibourhood-spark.sql("select neighbourhood_group, neighbourhood,price
from listing_temp_tbl where room_type = 'Shared room' order by price asc limit 5")
df avgpricebyneibourhood-spark.sql("select neighbourhood_group, neighbourhood,price
from listing_temp_tbl where room_type = 'Entire home/apt' order by price asc limit 5")
df avgpricebyneibourhood-spark.sql("select neighbourhood_group, neighbourhood,price
from listing_temp_tbl where room_type = 'Entire home/apt' order by price asc limit 5")
df avgpricebyneibourhood.show()
|neighbourhood_group|neighbourhood|price|
        Central Region|Marine Parade| 14|
         Central Region| Geylang|
                                                         15
         Central Region|
                                          Outram
                                   Tampines|
            East Region|
             West Region| Jurong West| 15|
+-----
|neighbourhood_group|neighbourhood|price|
+-----
             East Region|
                                          Bedok| 14|
             West Region| Jurong West|
         Central Region|
                                   Kallang|
                                                          18
         Central Region
                                         Rochorl
                                                          181
        Central Region|
                                         Kallang| 19|
|neighbourhood_group|neighbourhood|price|
         Central Region|
         Central Region|
                                        Geylang| 14|
            West Region|Bukit Panjang|
                                                          141
         Central Region| Bukit Timah|
           North Region|
```

4)6. Percentage of owners who rent more than one property (As a pie chart).



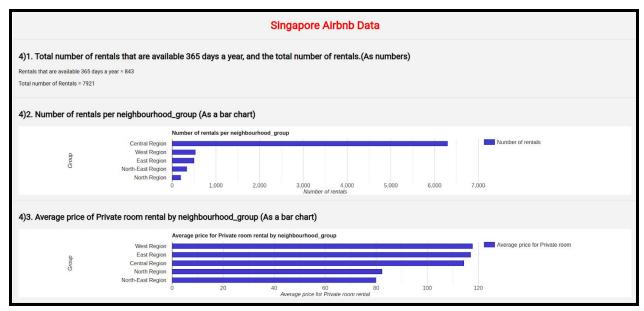
4)7. Histogram of number of rentals reviewed over time (based on last_review) in mouth granularity (As a bar chart).



4)8. Number of rentals that are available all 365 days of the year for each neighbourhood, that are in the neighbourhood which have top 5 average rental prices (As a table).



Following is the web dashboard created to represent the data.

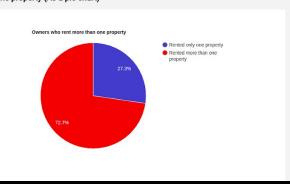


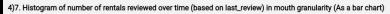
lo.	Neighbourhood group	Neighbourhood	Average price
	Central Region	Southern Islands	649.67
	Central Region	Marina South	419.0
	West Region	Bukit Panjang	409.45
	West Region	Jurong East	182.26
	Central Region	Downtown Core	163.50
	Central Region	Singapore River	150.67
	Central Region	Orchard	146.90
	Central Region	Toa Payoh	142.78
	Central Region	Bishan	138.92

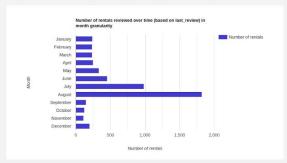
	om					
Ivate Roo						
No.	id	host id	host name	Neighbourhood group	Neighbourhood	Price
	18679631	108408404	Sutthida	Central Region	Marine Parade	14
	21926382	45343820	Deqing	East Region	Tampines	15
1	33324090	13503463	Angelina	West Region	Jurong West	15
1	10318835	13460992	Ming	Central Region	Geylang	15
5	24883645	14021375	Marc	Central Region	Outram	15
itire hom	no/ant					
uie nom	е/арт					
No.	id	host id	host name	Neighbourhood group	Neighbourhood	Price
	21408571	114674497	Mitul	Central Region	Rochor	0
!	37506711	29799617	John	Central Region	Geylang	14
3	35947264	75175440	Rain	West Region	Bukit Panjang	14
	16381367	26246420	Jordan	Central Region	Bukit Timah	31
4	10301307			_		

Shared roo	Shared room					
No.	id	host id	host name	Neighbourhood group	Neighbourhood	Price
1	18656726	21900076	Mary	East Region	Bedok	14
2	22034488	160839396	Bi	West Region	Jurong West	15
3	26170424	196709892	Anna	Central Region	Rochor	18
4	10040828	46545593	Meadows	Central Region	Kallang	18
5	20839977	63448912	River City Inn	Central Region	Singapore River	19

4)6. Percentage of owners who rent more than one property (As a pie chart)







4)8. Number of rentals that are available all 365 days of the year for each neighbourhood, that are in the neighbourhood which have top 5 average rental prices (As a table)

No.	Neighbourhood group	Neighbourhood	Average price
1	West Region	Western Water Catchment	1
2	West Region	Bukit Panjang	1
3	North Region	Woodlands	12
4	North-East Region	Serangoon	8
5	North Region	Lim Chu Kang	1

[REFERENCES]

[1]https://www.xenonstack.com/blog/big-data-ingestion/