BIG DATA ANALYTICS REPORT - INDIVIDUAL PROJECT 2

STUDYING ABROAD: FACTORS INVOLVED

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Pratik Shirish Kamath (N14671569)

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1 ABSTRACT

Studying abroad is not only academically and culturally fulfilling, but also fosters personal growth. It is not only a good experience seeing and exploring a new country, but learning to interact with people from a variety of cultural background and learning from a curriculum you design is somewhat every student expects to take out from studying abroad. There are many factors, however, which affect the number of students going abroad for studying namely GDP, percentage of GDP invested by country on education etc. In this project, I have managed to venture into few of these factors and bring about conclusive results as to which factors are the most responsible[1].

2 Introduction

For this project, I have used HIVE and MySQL for pre-processing the data i.e students abroad, gdp for countries, percentage of GDP invested in education datasets. I have created the tables in MySQL witht the same "skeleton-structure" as that of our datasets involved and loaded the data in the tables. After that I created an index(ID) for the tables using concatenation of country and year.

After that, I then imported them in HIVE and performed a join operation on them. This table was then used for Machine Learning and Information visualization analysis in R. Also, I have used Map Reduce analysis in Cloudera Hadoop environment for categorizing the output on basis of country using Apache Pig.

3 SQL Preprocessing

First of all I created tables in SQL for students studying abroad, GDP and %age of GDP invested in education as follows. Then I loaded the data in them using UNESCO datasets. After that, I created an index using country and year columns to create an ID for these tables so that the procedure of joining the tables becomes easier. Here in this way I have demonstrated effective data manipulation so that I will get all the statistics for a given country according to it's year because we need yearwise distribution for a country. I have concatenated two main factors which are important and made a new key which can be used as a primary index and can be used to join the tables which otherwise would have been very difficult to join. As seen from the figures, I have created skeletons of tables, loaded data from the UNESCO datasets and exported them as .txt files.

Figure 1

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Figure 2

Figure 3

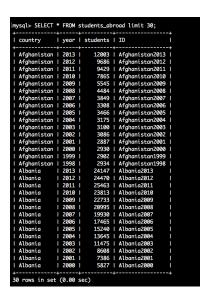


Figure 4

mysql> SELECT * FROM students_abroad INTO OUTFILE '/tmp/students_abroad.txt' FIELDS TERMINATED BY '\t' OPTIONALLY ENCLOSED BY ''' LINES TERMINATED BY '\n'; Query OK, 3264 rows affected (0.00 sec)

Figure 5

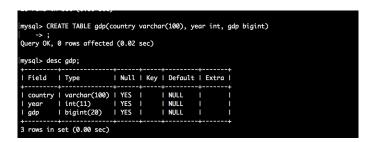


Figure 6

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Records: 18079 - Deleted: 0 Scipped: 0 Mornings: 18084
myscio. ||

Figure 7

Figure 8

Figure 9

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Figure 10

4 HIVE PREPROCESSING

Here, similar to the skeleton created in SQL I have created skeleton-structure of the table. After that I used the three .txt files I had exported from MySQL and loaded them in the tables.Now we know that we have an ID field which is common in all the tables and the join operation can now be done easily and therefore I proceeded to do the join operation using the ID field as primary index for all the tables.

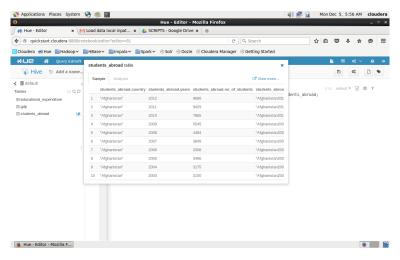


Figure 11

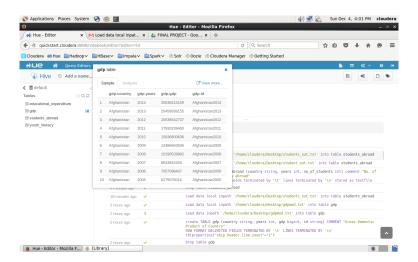


Figure 12

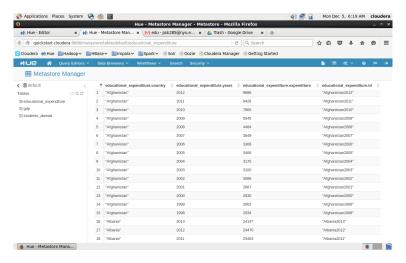


Figure 13

The .txt files exported were as follows:

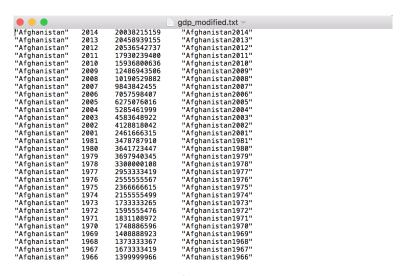


Figure 14

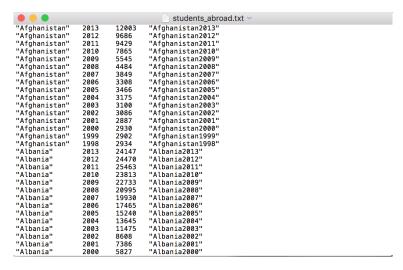


Figure 15

```
| Afghanistan | 2013 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 | 12003 |
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Figure 16

```
create table students_abroād (country string, years int, no_of_students int, id string) comment "No. of students going to study abroad" row format delimited fields terminated by '\n' lines train of lines ("stip, header.line.count"="1");

create TABLE gdp (country string, years int, gdp bigint, id string) COMMENT "Gross Domestic Product of Country" ROW FORMAT DELIMITED BY '\n' lines TREMINATED BY '\n' lines ("skip.header.line.count"="1");

Load data local inpath '/home/cloudera/Desktop/gdp_modified.txt' into table gdp;
Load data local inpath '/home/cloudera/Desktop/students_abroad.txt' into table students_abroad;
Load data local inpath '/home/cloudera/Desktop/education_expenditure.txt' into table educational_expenditure;

select students_abroad.country as country, students_abroad.years as years, students_abroad.number_of_students as students,
gdp as gdp, educational_expenditure.expenditure as expenditure
from students_abroad.mod lexpenditure on (educational_expenditure.id = students_abroad.id)

30IN educational_expenditure on (educational_expenditure.id = students_abroad.id)

### On Terminal: To export the joined data as a CSV.
hive —e'select * from main_data' > /home/cloudera/Desktop/main_data.csv
```

Figure 17

Above I have mentioned all the commands I used in HIVE to do the preprocessing and after the join operation was completed I exported it as a csv for further Map Reduce and Machine Learning analysis.

country	years	students	gdp	expenditure	
Afghanistan	2013	12003	2.0459E+10	4.57999992	
Afghanistan	2012	9686	2.0537E+10	3.13000011	
Afghanistan	2011	9429	1.793E+10	4.09000015	
Afghanistan	2010	7865	1.5937E+10	4.51000023	
Albania	2013	24147	1.2781E+10	3.5	
Albania	2007	19930	1.0701E+10	3.26999998	
Albania	2006	17465	8992642349	3.1099999	
Albania	2005	15240	8158548717	3.1500001	
Albania	2004	13645	7314865176	3.1099999	
Albania	2003	11475	5746945913	3.11999989	
Albania	2002	8608	4435078648	3.04999995	
Albania	2001	7386	4060758804	3.31999993	
Albania	2000	5827	3632043908	3.24000001	
Albania	1999	4685	3414760915	3.3599999	
Albania	1998	4596	2707123772	3.29999995	
Algeria	2008	21987	1.71E+11	4.34000015	
Andorra	2013	1177	3249100675	2.46000004	
Andorra	2011	1377	3427235709	3.16000009	
Andorra	2010	1249	3346317329	3.06999993	
Andorra	2009	1314	3649863493	3.16000009	
Andorra	2008	1200	4001349340	2.93000007	
Andorra	2007	991	4010785102	2.06999993	
Andorra	2006	305	3536451646	2.19000006	
Andorra	2005	1085	3248134607	1.60000002	
Andorra	2004	1224	2916913449	1.52999997	
Andorra	2002	714	1717563533	1.70000005	
Angola	2010	7916	8.3369E+10	3.48000002	
Angola	2006	8268	5.2381E+10	2.8599999	
Angola	2005	8020	3.6971E+10	2.77999997	
Angola	2000	5359	9129634978	2.6099999	

Figure 18

The final csv after SQL and HIVE preprocessing looks as shown above. However we need to do effecttive grouping now which can be done using Map Reduce analysis which I have achieved through Apache Pig in Cloudera Hadoop environment and Machine learning and Information visualization which I have done using R.

5 MAP REDUCE ANALYSIS

For Map Reduce analysis, I used Apache Pig in Cloudera Hadoop environment which is basically an abstraction for the Java backend. It made my M/R easy to implement and made it equally effective. The basic need to do map reduce analysis was to group the data according to the factor of our choice. Here I have used country as the factor of choice and generated a count for the countries so that we come to know how many values are there for a particular country as well. The Apache Pig script I wrote for that was as follows:

Figure 19

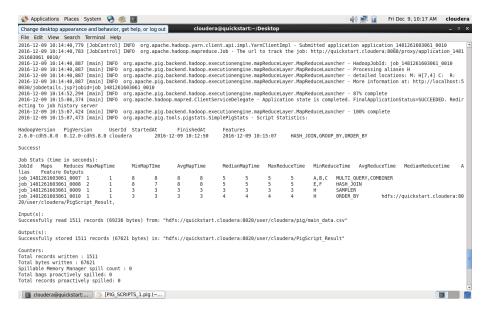


Figure 20

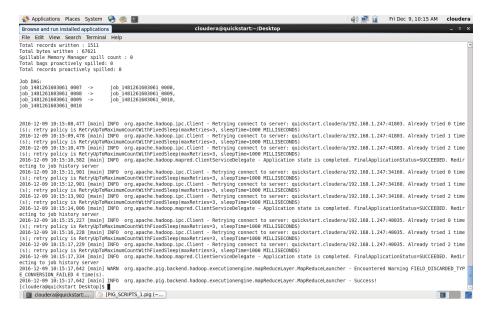


Figure 21

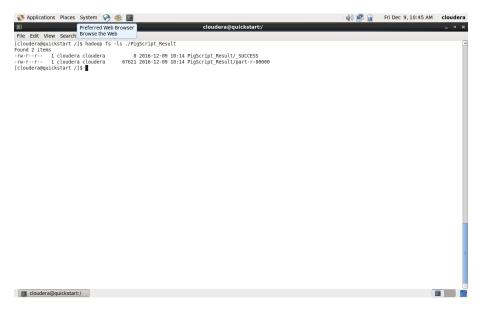


Figure 22

The final output that I generated through Pig is as follows which has count for each country as well. Thus I have successfully implemented Map Reduce analysis with my dataset. However I also wanted to do a machine learning analysis to analyze as to how the factors affect the number of students as I have done that analysis in R and all I have done is mentioned in my next section.

```
Cuba 2007 1442 58603500000 11.87 6
Cuba 2010 2119 64328200000 12.84 6
Cuba 2009 1755 62078600000 13.13 6
Cuba 2008 1592 60806300000 14.06 6
Cuba
     2004
          1199 38202800000 10.27 6
Cuba 2006 1380 52742100000 9.06 6
     2013 14204 201848000000
Peru
                                 3.28
                                      6
Peru 2005 10134 74947898080 2.88 6
Peru 2007 13374 102171000000
                                 2.63
                                      6
Peru 2009 15601 121192000000
                                 3.13
                                      6
Peru 2011 16424 170564000000
                                 2.68
Peru 2012 15083 192680000000
                                 2.92 6
Chile 1999 4696 72995286764 3.84 15
Chile 2000 5070 79328640264 3.71 15
Chile 2013 8937 276674000000
                                 4.56
                                      15
Chile 2012 8924 265232000000
                                 4.57
                                      15
Chile 2011
          9860 250832000000
                                 4.07
                                      15
Chile 2010 9127 217538000000
                                 4.18
                                      15
Chile
     2009
          8242 171957000000
                                 4.24
                                      15
Chile
     2008 7120 179627000000
                                 3.79
                                      15
Chile 2007 6177 173081000000
                                 3.22 15
```

Figure 23

6 MACHINE LEARNING

As mentioned before I have done the Machine Learning and information visualization in R. Below are the graphs and explanation as to which Machine learning analysis I have applied to them.

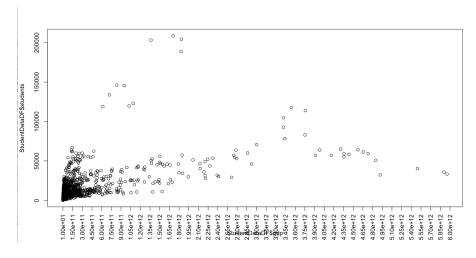


Figure 24

The graph above shows the variation of number of students each year w.r.t to GDP of country they belong to. this clearly shows that the number of students going abroad are densely populated in countries with lower GDP. We can say that no of students is inversely proportional to GDP of country which might be true because if there is high GDP there is high probability that there are adequate employment opportunities in those countries and vice-a-versa can be assumed too.

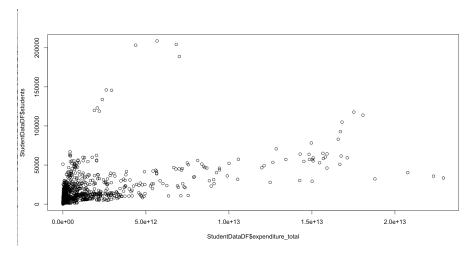


Figure 25

As the expenditure of the countries on education was given as a percentage of GDP, I calculated the expenditure for all the countries as expenditure_total = expenditure in percentage x GDP of the country and found out the values of expenditure and I plotted them as a function of students going abroad which is showing similar results.

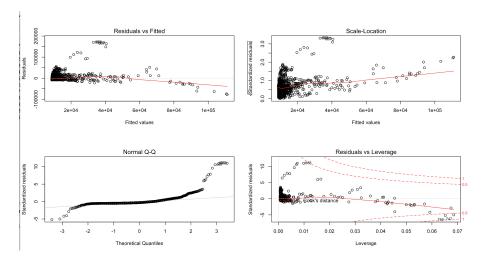


Figure 26

The above figure shows the plot of the regression analysis[4] I did using GDP and expenditure as factors of number of students going abroad. I had got R-squared value to be around 0.33 which shows there is good correlation but there might be other factors which might be needed to get better results. After that I did a 10 fold cross-validation[3] and still got a R-squared result more than 0.3 showing that my model is consistent.[5]

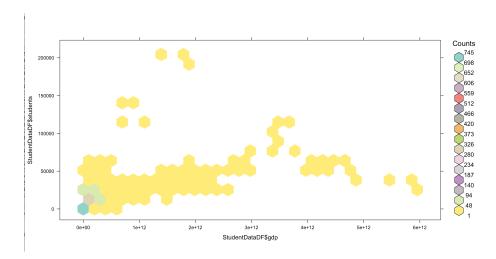


Figure 27

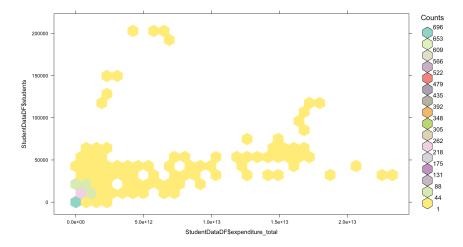


Figure 28

Above are hexbin plots which categorize on basis of colors and give an accurate result. I plotted number of students w.r.t GDP and expenditure respectively and the graphs above demonstrate that. As expected higher concentration of students going abroad lying in countries with lower gdp and lower expenditure on education.

The graph below shows variation of number of students w.r.t years with the mean plotted for all years showing it has almost been the same over the years[2].

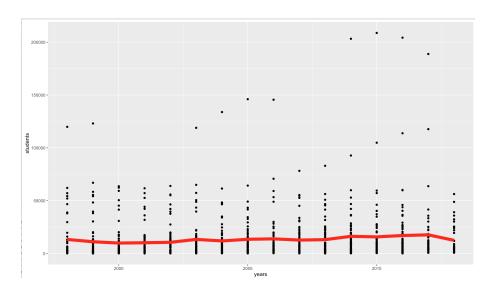


Figure 29

7 CONCLUSION

In this way I used UNESCO datasets for number of students going abroad, GDP of countries and expenditure of countries on education as percentage of their GDP for doing Map Reduce analysis in Apache Pig using Cloudera Hadoop environment and also managed to analyze trends of these factors using supervised Machine Learning in R and did some interesting information visualization as well.

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