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# GuineaPig Naive Bayes for 10605 15 Fall

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## 1 Question 1

I did not receive direct help from others. I did not give detailed direct help to others.

## 2 Question 2

We could use following steps to generate the required output:

**Step 1**, Group all the files to get the fg count. Using GuineaPig like representation:

```
fgCount=Group(by=lambda (n,y,c):y=1960,reducingTo=ReduceToCount)
```

**Step2**, Group all the files to get the bg count. Using GuineaPig like representation:

```
bgCount=Group(by=lambda (n,y,c):y>1960,reducingTo=ReduceToCount)
```

**Step3**, After getting the two tables, we could join the two tables by the word names and then map it to the format we want:

```
joined=Join(Jin(fgCount, by=lambda (n,y,c):n), Jin(bgCount, by=lambda (n,y,c):n))
```

```
output= Map(joined, by=formatting)
```

After these three steps, we could get the formatted output as required.

## 3 Question 3

### 3.1 (a)

The figure is as follows, the runtime is measured in seconds.

### 3.2 (b)

As we could see from the figure above, the program is not perfectly scalable. The running time would not halves if the number of worker machine is doubled. This was due to several reasons. First of all, sperating data to different machines would cost extra running time compared with running on a single machine. Besides, when it comes to distributed computing paradigm, the synchronization would always take extra time. When we need do the whole corpus reducing, faster machines would need to wait for slow machines to finish their mapping or combining job, then started reducing jobs.

For my program, in the mapping step, I scanned twice the whole corpus to get all the parameters and counts. The faster machines would wait for the slower machines in these two scans for next actions. Then the join step, it would cost extra time to distribute data to different machines

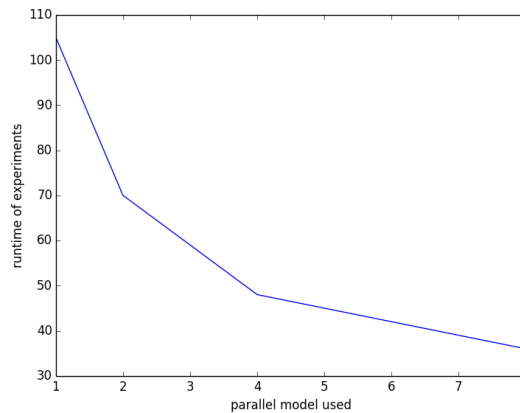


Figure 1: runtime vs. parallel models

## 4 Question 4

This is a quiet interesting problem. We should treat the two tables as streams in order to process the dataset in limited memory. So just like we are processing data between Map and Reduce steps in Hadoop, we need to sort the data, and then read the data stream. In order to get the distinct products, we could also sort the productId, or we could use a set to store distinct value. To get the counts, we need previous keys to store the past value and compare with current value.

**Step 1.** Sort two tables. The time complexity is  $O(n_1 \log n_1 + n_2 \log n_2)$   $n_1, n_2$  is table size. We could also only sort one table, and then stream another table and binary search the key in the sorted table. This would cost  $(n_1 \log n_1)$ .

**Step 2.** Loop sorted tables. Then we could read the stream data from the two sorted tables. We first read id1 from table1 and get name. Then we read id2 from table2. If the id1 == id2, go to Step 3. If id1 < id2, id1++. If id1 > id2, id2++. Loop the two sorted table would be  $O(n_1 + n_2)$ . If we only sorted one data, and use binary search here, then the time would be  $O(n_2 \log n_1)$

**Step 3.** Get distinct products count. If id1 matches id2, then we could get the distinct products that person bought. We could first sort and then loop the productIds. If the previousKey does not equal currentKey, then add one to the count. This would cost  $O(m \log m + m)$  for time, and  $O(1)$  for space. We could also use a set to store different productIds. This would cost  $O(m)$  for time, but  $O(m)$  for space.

With these three steps, we could implement the Join and Distinct functions in GuineaPig, getting name and distinct count. The time complexity is about  $O(n \log n + n)$  and with limit space complexity, which are acceptable.

## 5 Question 5

The meaning of each python code line is :

**L1** doc = ReadLines('data.txt') — Map(by=lambda line:line.split(" "))

This line would read data and then split each line via space into a list.

**L2** t1 = Flatten(doc, flat1)

This line get the even index word from the splited doc

**L3** t2 = Flatten(doc, flat2)

This line get the odd index word from the splited doc

**L4** `t3 = Join(Jin(t1), Jin(t2)) | ReplaceEach(by=lambda(w1,w2):(w1+w2,len(W2)))`

This line would first join the two views, and get a word tuple. The first element is the even index word, and the second element is the nearest bigger odd index word. Then it would map the joined table to a new tuple. The new first element is the word1 + word2, the new second element is the length of word2.