Lab 2 – Alternative solutions

Lab 2

- Input file

  A1008ULQSWI006,**B**0017OAQIY
  A100EBHBG1GF5,B0013T5YO4
  A1017Y0SGBINVS,B0009F3SAK
  A101F8M8DPFOM9,B005HY2BRO,B000H7MFVI
  A102H88HCCJJAB,B0007A8XV6
  A102ME7M2YW2P5,B000FKGT8W
  A102QP2OSXRVH,B001EQ5SGU,B000EH0RTS
  A102TGNH1D915Z,B000RHXKC6,B0002DHNXC,B0002DHNXC,B000XJK7UG,B00008DFK5,B000SP1CWW,B0009YD7P2,B000SP1CWW,B00008DFK5,B0009YD7P2
  A1051WAJL0HJWH,B000W5U5H6
  A1052V04GOA7RV,B002GJ9JY6,B001E5E3JY,B008ZRKZSM,B002GJ9JWS
  .....

- Each line contains
  - a reviewer ID (**A**XXXXXX) and
  - the list of products reviewed by her/him (**B**XXXXXX)

Lab 2 – Ex. 1

- Your goal is to find the top 100 pairs of products most often reviewed (and so bought) together
- We consider two products as reviewed (i.e., bought) together if they appear in the same line of the input file

Lab 2 – Ex.1: Possible solutions

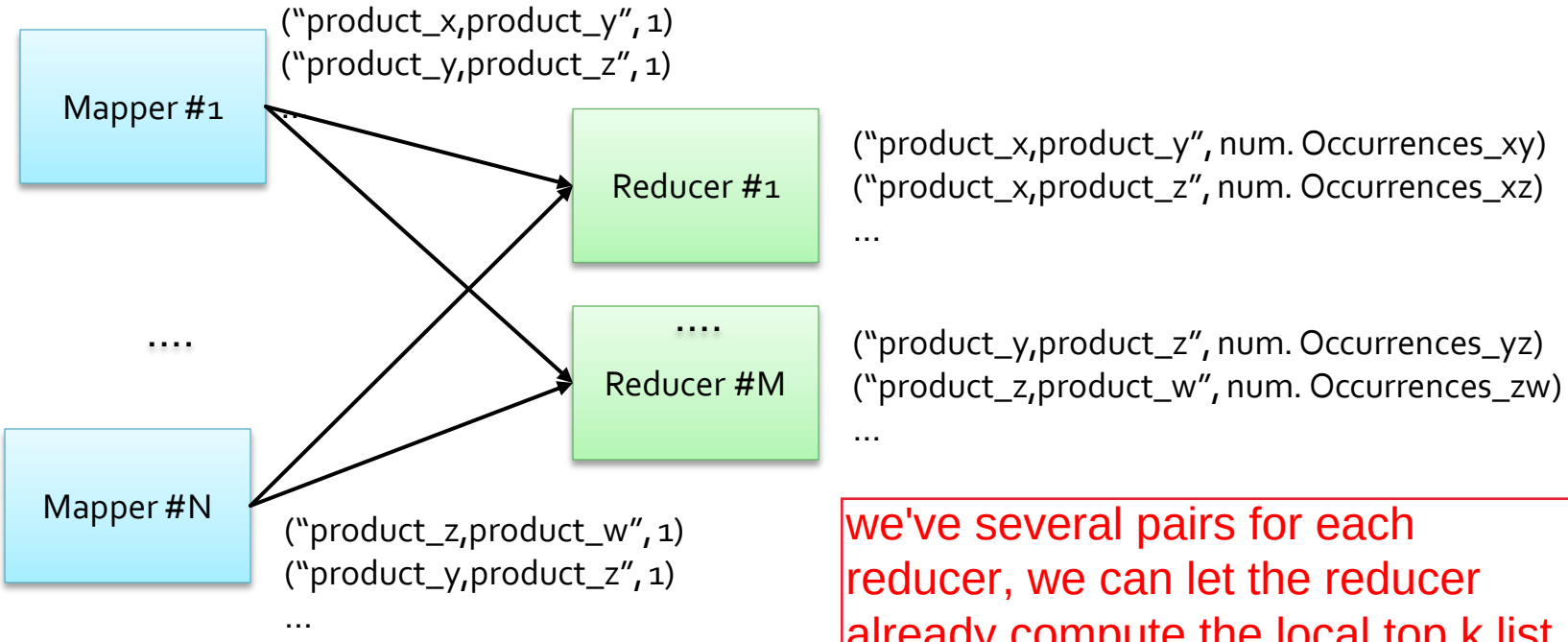
- At least three different "approaches" can be used to solve Ex. 1 of Lab 2

Lab 2 – Ex.1: Solution #1

1. A chain of two MapReduce jobs is used
   - The first job computes the number of occurrences of each pair of products that occur together in at least one line of the input file
     - It is like a word count where each "word" is a pair of products
   - The second job, selects the top-k pairs of products, in terms of num. of occurrences, among the pairs emitted by the first job
     - It implements the top-k pattern

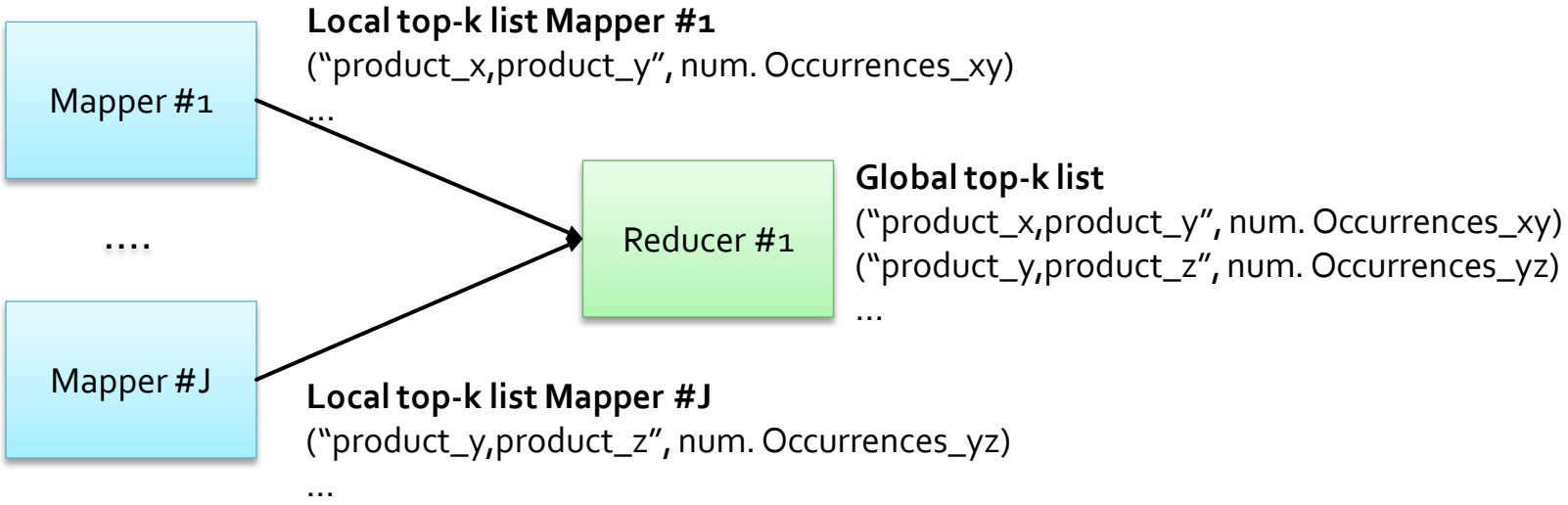
Lab 2 – Ex.1: Solution #1

- The first job computes the number of occurrences of each pair of products analyzing the input file



Lab 2 – Ex.1: Solution #1

- The second job computes the global top-k pairs of products in terms of num. of occurrences



Lab 2 – Ex.1: Solution #2

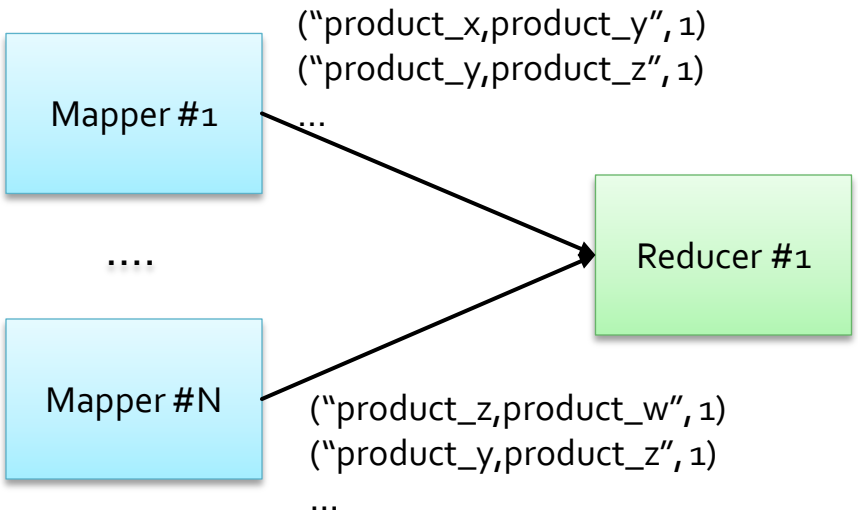
2. One single MapReduce jobs is used
   - The job
     - Computes the number of occurrences of each pair of products that occur together in at least one line of the input file
       - It is again like a word count where each "word" is a pair of products
       - However, the reducer does not emit all the pairs (pair of products, #of occurrences) that it computes
         - The top-k list is computed in the reducer and is emitted in its cleanup method

Lab 2 – Ex.1: Solution #2

- In the reducer, the job computes **also** the top-k list
  - By initializing the top-k list in the setup method of the reducer
  - By updating the top-k list in the reduce method (immediately after the computation of the frequency of the current pair of products)
  - By emitting the final top-k list in the cleanup method of the reducer
- There must be **one single reducer** in order to compute the final global top-k list

Lab 2 – Ex.1: Solution #2

- There is one single job that computes the number of occurrences and the global top-k list at the same time in its single reducer



Global top-k list
("product_x,product_y", num. Occurrences_xy)
("product_y,product_z", num. Occurrences_yz)
...

we're not parallelyzing and the reduce does more task

Lab 2 – Ex.1: Solution #3

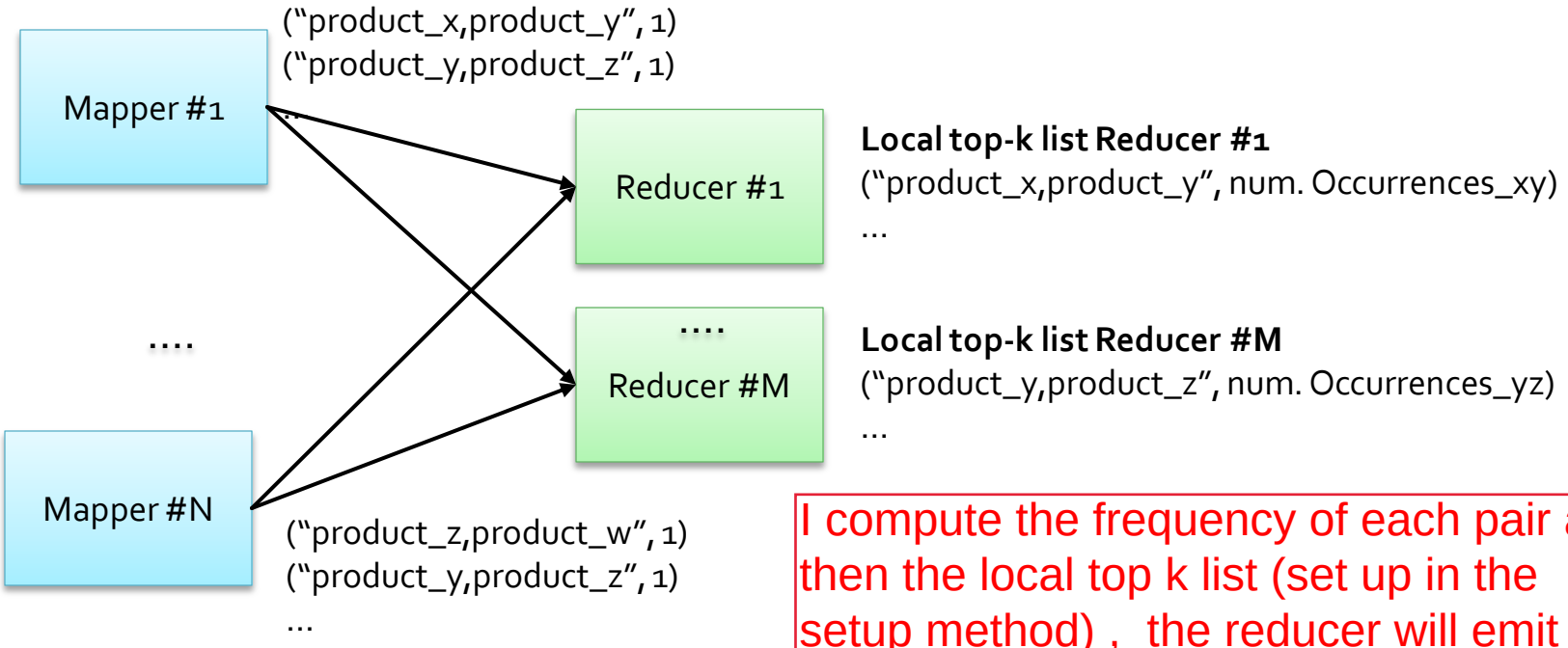
3. A chain of two MapReduce jobs is used
   - The first job is the same job used by Solution #2
     - However, in this case the number of reducers is set to a value greater than one
       - This setting allows parallelizing this intermediate step
     - Each reducer emits a local top-k list
       - The first job returns a number of local top-k lists equal to the number of reducers of the first job

Lab 2 – Ex.1: Solution #3

- The second job computes the final top-k list merging the pairs of the local top-k lists emitted by the first job
  - It is based on the standard Top-k pattern

Lab 2 – Ex.1: Solution #3

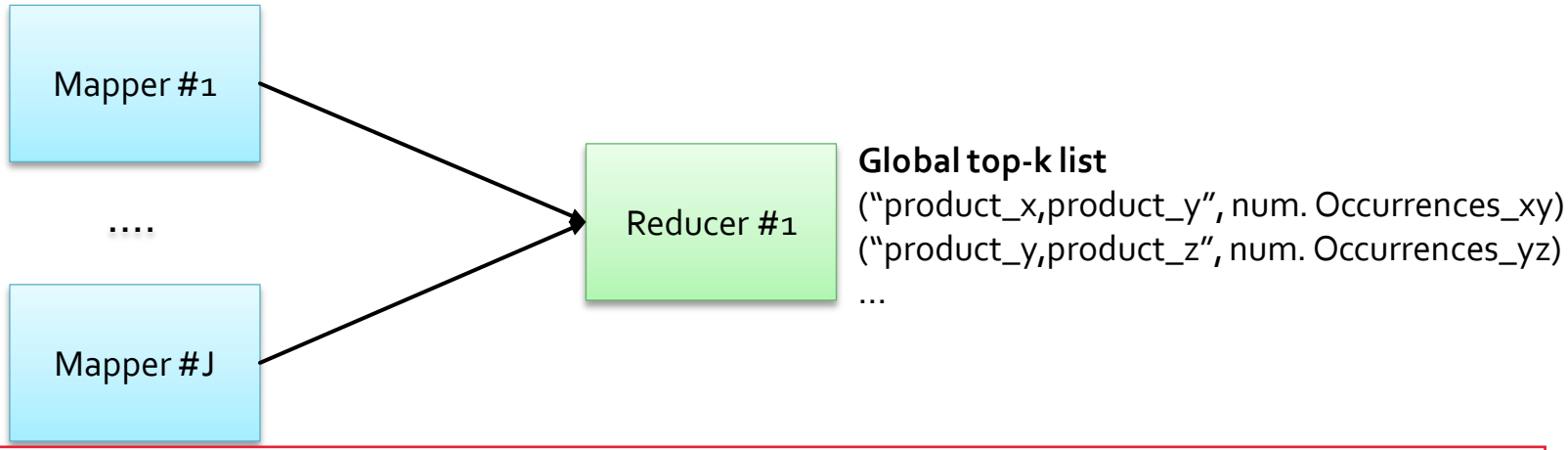
- The first job computes the number of occurrences of each pair of products but each reducer emits only its local top-k pairs



I compute the frequency of each pair and then the local top k list (set up in the setup method) , the reducer will emit a lower number of data

Lab 2 – Ex.1: Solution #3

- The second job computes the global top-k pairs of products in terms of num. of occurrences merging the local list of job #1



only the instance of the reducer will compute the global top k list,
the map phase simply create a copy of the input, because in the first job the top k list has already been computed in the reduce phase. (reduce only job doesn't exist.

Lab 2 – Ex.1: Comparison of the proposed solutions

- Solution #1
  - +Adopts two standard patterns
  - - However, the output of the first job is very large
    - One pair for each pair of products occurring together at least one time in the input file

GOOD AT THE EXAM , NOT IN REALITY
-we can use a combiner for the first job, in the second job is useless
-but the combiner CAN'T compute the top k list because there are pairs that appear in the second instance of the mapper

Lab 2 – Ex.1: Comparison of the proposed solutions

- Solution #2
  - +Only one job is instantiated and executed (there is only one job in Solution #2) and its output is already the final top-k list
  - - However, only one reducer is instantiated
    - It could become a bottleneck because one single reducer must analyze the potentially large set of pairs emitted by the mappers
  - - It is not a standard pattern

Higly inefficient , to be not done at the exam
-we can use a combiner for each instance of the mapper, but the combiner CAN'T compute the top k list because there are pairs that appear in the second instance of the mapper

Lab 2 – Ex.1: Comparison of the proposed solutions

- Solution #3
  - +Each reducer of the first job emits only the pair contained in its local top-k lists
    - One top-k list for each reducer
    - The pairs of the top-k lists emitted by the reducers are significantly smaller than all the pairs of products occurring together at least one time
    - Since the first job instantiates many reducers, the parallelism is maintained
  - - It is not a standard pattern

The most efficient one for lab2