Simultaneous scheduling of data replication and computation in Grids

Frédéric Desprez, Antoine Vernois

Laboratoire de l'Informatique du Parallélisme
École Normale Supérieure de Lyon, France

CLADE 2005
July, 24th 2005

Agenda

1. Motivations
2. Model
3. Simulations et results
4. Conclusions

Agenda

Context : bioinformatic application

- reference databanks
  - "flat" text files
  - few MB to several GB
  - update : daily to monthly
  - number and size of data increase very quickly
- requests
  - one algorithm applied to one or two databanks

Context : bioinformatic application

- reference databanks
  - "flat" text files
  - few MB to several GB
  - update : daily to monthly
  - number and size of data increase very quickly
- requests
  - one algorithm applied to one or two databanks

Context : bioinformatic application

- reference databanks
  - "flat" text files
  - few MB to several GB
  - update : daily to monthly
  - number and size of data increase very quickly
- requests
  - one algorithm applied to one or two databanks

Logs analysis

From log files of an existing bioinformatic portal :

- some requests are more frequent than other
  - blast over sp.fas : 77% of requests
- the usage of databanks and kind of requests is constant.

Logs analysis

From log files of an existing bioinformatic portal :

- some requests are more frequent than other
  - blast over sp.fas : 77% of requests
- the usage of databanks and kind of requests is constant.

Logs analysis

From log files of an existing bioinformatic portal :

- some requests are more frequent than other
  - blast over sp.fas : 77% of requests
- the usage of databanks and kind of requests is constant.

We can start from the study of previous usage schemes.

Some figures

extract from logs of NPS@, bioinformatic web portal :

Number of databanks	23
Number of algorithms	8
Number of couple algorithm-databanks	80
Size of the smallest databank	1 MB
Size of the largest databank	12 GB

Replicate databanks

Goal :

- improve computation time,
- and/or platform throughput.

Data sets are initially stored on public server :

- insert them into the grid
- keep them up to date
- prevent bottleneck

Replicate databanks

Goal :

- improve computation time,
- and/or platform throughput.

Data sets are initially stored on public server :

- insert them into the grid
- keep them up to date
- prevent bottleneck

Question : Where and when create replicas ? ?

A simple idea

Store all databanks on each server.

- not always possible : too many data
- too much space occupied by useless databanks
  - databanks are not all used at all the time. (embl.fas = 12 Gb, $< 1\%$ of requests)
- updating databanks become costly

Usually

- scheduling and replication are two independant processes,
- replication has to be done by users,
- schedulers don't take care of locality of data.

Usually

- scheduling and replication are two independant processes,
- replication has to be done by users,
- schedulers don't take care of locality of data.

Usually

- scheduling and replication are two independant processes,
- replication has to be done by users,
- schedulers don't take care of locality of data.

Usually

- scheduling and replication are two independant processes,
- replication has to be done by users,
- schedulers don't take care of locality of data.

An idea :

Usually

- scheduling and replication are two independant processes,
- replication has to be done by users,
- schedulers don't take care of locality of data.

An idea :

Join scheduling of computation and replication of data

Agenda

Things we know

- platform
  - n computation servers P_i
    - storage space : m_i
    - computation power : w_i
- bioinformatic
  - m databanks d_j of size : $size_j$
  - p algorithms a_k :
    - linear with size of databanks : $\alpha_k * size + c_k$
  - requests $R(k, j)$
    - usage frequency : $f(k, j)$

Things we know

- platform
  - n computation servers P_i
    - storage space : m_i
    - computation power : w_i
- bioinformatic
  - m databanks d_j of size : $size_j$
  - p algorithms a_k :
    - linear with size of databanks : $\alpha_k * size + c_k$
  - requests $R(k, j)$
    - usage frequency : $f(k, j)$

Things we know

- platform
  - n computation servers P_i
    - storage space : m_i
    - computation power : w_i
- bioinformatic
  - m databanks d_j of size : $size_j$
  - p algorithms a_k :
    - linear with size of databanks : $\alpha_k * size + c_k$
  - requests $R(k, j)$
    - usage frequency : $f(k, j)$

Things we have to determine

- TP : throughput
- δ_i^j : placement of databanks
- $n_i(k, j)$: requests done by each server
  - number of jobs $R(k, j)$ done by P_i : $n_i(k, j)$

Constraint

- each data at least on one server
- a server cannot store more than availaible space
- a server cannot compute more than availiable computation power
- a request can be executed only if data is on the server
- job distribution follow usage frequency

Constraint

- each data at least on one server
- a server cannot store more than availaible space
- a server cannot compute more than availiable computation power
- a request can be executed only if data is on the server
- job distribution follow usage frequency

Constraint

- each data at least on one server
- a server cannot store more than availaible space
- a server cannot compute more than availiable computation power
- a request can be executed only if data is on the server
- job distribution follow usage frequency

Constraint

- each data at least on one server
- a server cannot store more than availaible space
- a server cannot compute more than availiable computation power
- a request can be executed only if data is on the server
- job distribution follow usage frequency

Constraint

- each data at least on one server
- a server cannot store more than availaible space
- a server cannot compute more than availiable computation power
- a request can be executed only if data is on the server
- job distribution follow usage frequency

Constraint

- each data at least on one server
- a server cannot store more than availaible space
- a server cannot compute more than availiable computation power
- a request can be executed only if data is on the server
- job distribution follow usage frequency

Goal : Maximize throughput of the platform (makespan)

Linear program

linear program formulation

MAXIMIZE TP,

WITH CONSTRAINTS

$$\begin{cases} (1)\ \sum_{j=1}^{n} \delta_i^j \geqslant 1 & 1 \leqslant i \leqslant m \\ (2)\ \sum_{j=1}^{n} \delta_i^j.size_j \leqslant m_i & 1 \leqslant i \leqslant m \\ (3)\ \sum_{k=1}^{p} \sum_{j=1}^{n} n_i(k,j)(\alpha_k * size_j + c_k) \leqslant w_i & 1 \leqslant i \leqslant m \\ (4)\ n_i(k,j) \leqslant v_{k,j}.\delta_i^j.\frac{w_i}{\alpha_k.size_j + c_k} & 1 \leqslant i \leqslant m, 1 \leqslant j \leqslant n, 1 \leqslant k \leqslant p \\ (5)\ \sum_{i=1}^{m} n_i(k,j) = f_{k,j}.TP & 1 \leqslant i \leqslant m, 1 \leqslant j \leqslant n \end{cases}$$

A word on solution

Integer and rational number problem

- use of integer approximation for δ_i^j

With realistic information, we can notice :

- the most used data are more replicated
- storage space is not full

Agenda

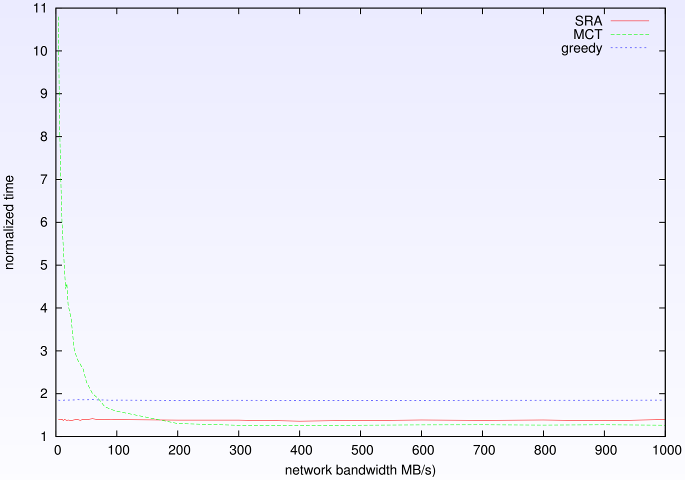
Simulation

- use of OptorSim
  - simulator for grid data management
  - developped for European DataGrid project
- largely modified to match our needs
  - heterogeneous compute system
  - batch scheduler
  - heterogeneous computation time
  - ...

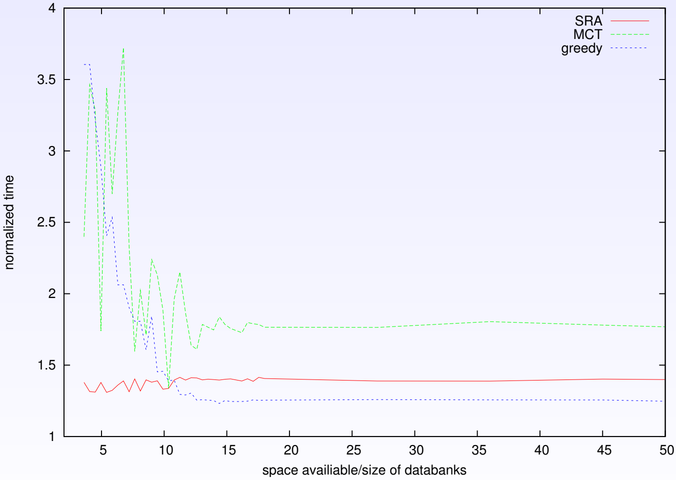
Tests

- test platform :
  - generated by Tiers
  - 10 platforms
- Requests :
  - based on real requests
  - 40000 requests

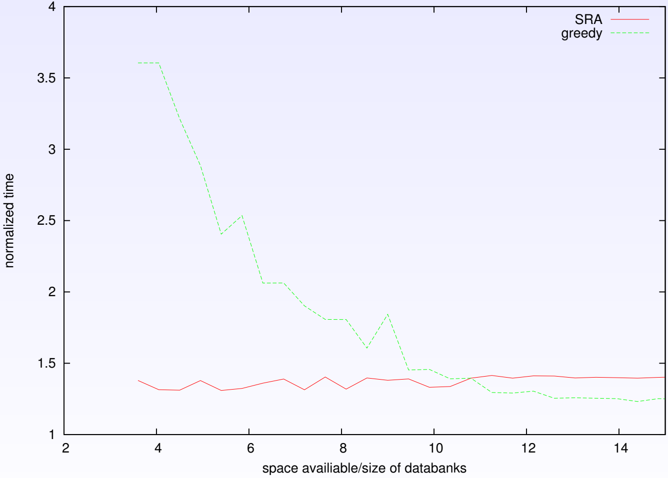
Execution time : fonction of network bandwidth



Execution time : function of storage space availiable



Execution time : function of storage space (zoom)



Agenda

1. Motivations
2. Model
3. Simulations et results
4. Conclusions
   - What have been done...
   - What is to be done...

Conclusions

- Steady state model
- Simulation
- Good optimisations for
  - low speed network
  - small storage space
- Placement is efficient

Work in progress

- Dynamic solution
- Real execution with DIET environment