



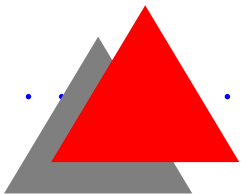
# *A branch-and-bound algorithm for the optimization of satellite observations*

Roberto Cordone

Federico Gandellini

Giovanni Righini

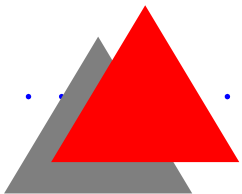
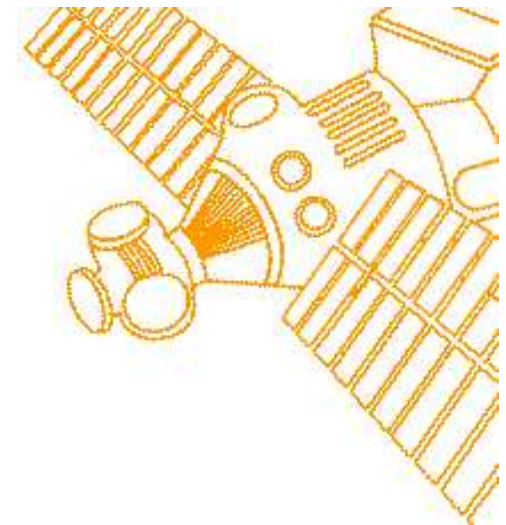
DTI - Università degli Studi di Milano (`cordone, righini@dti.unimi.it`)





# An overview

- **Nadir observations** and Polar Operational Environmental Satellites (*POES*)
- The **Swath-Segment Selection Problem** (*SSSP*)
- **An IP formulation**
- **Lagrangian bounding** procedures:
  - Subgradient ascent
  - Lagrangian heuristic
- A **branch-and-bound** algorithm
- **Experimental results** (random instances)
  - Small instances (branching performed)
  - Large instances (gap at the root node)

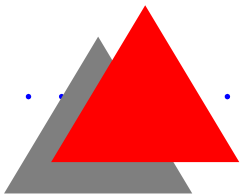




# Satellite observations

Satellites observations have several applications

- Leading meteorological observations (MetOp and COSMOSkyMed)
- Studying the Earth gravitational field and the geoid morphology (GOCE)
- Building extremely detailed maps (GLOBCOVER)

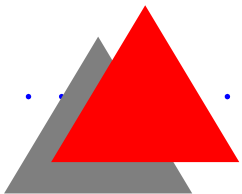
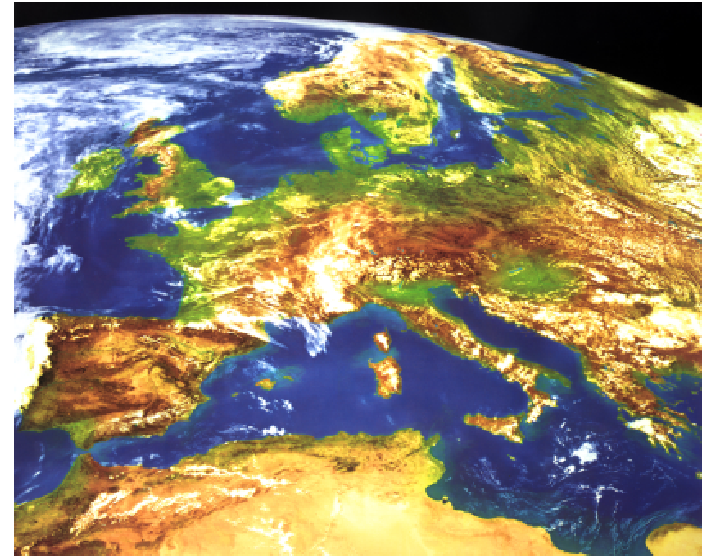




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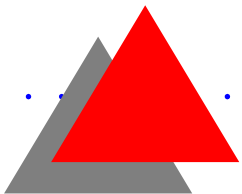
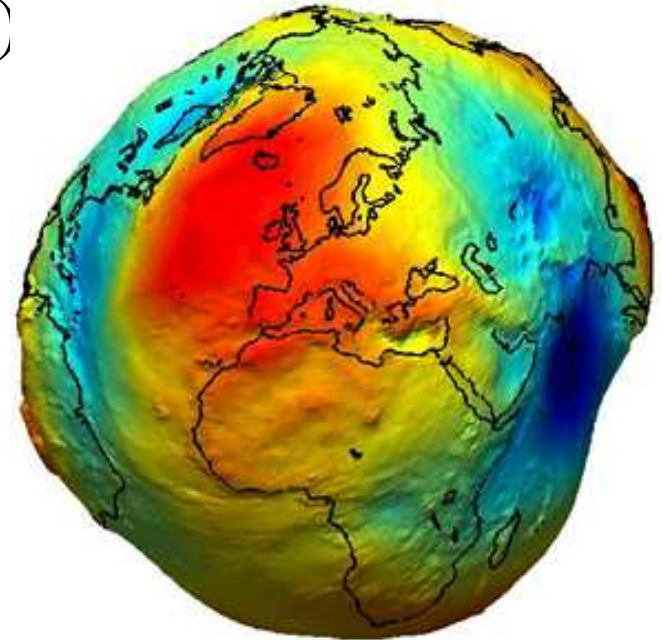
- Leading **metereological observations** (MetOp and COSMOSkyMed)
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# Satellite observations

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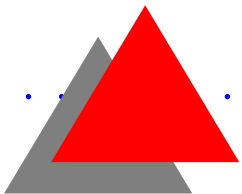
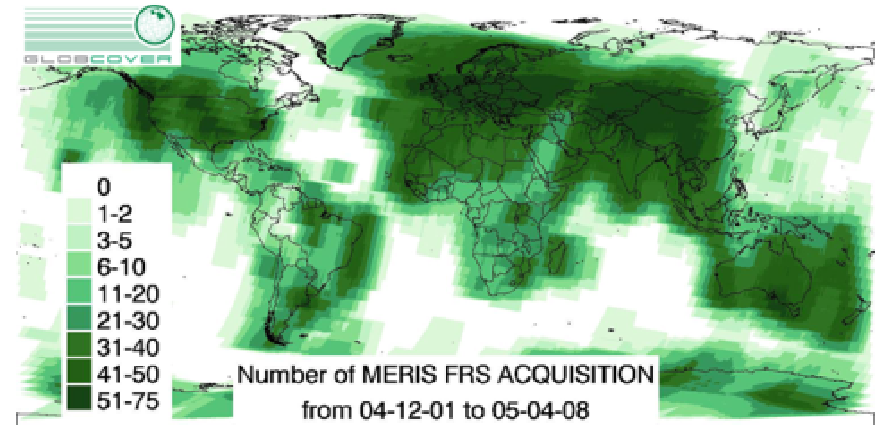
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# Satellite observations

Satellites observations have several applications

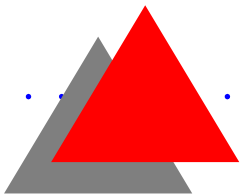
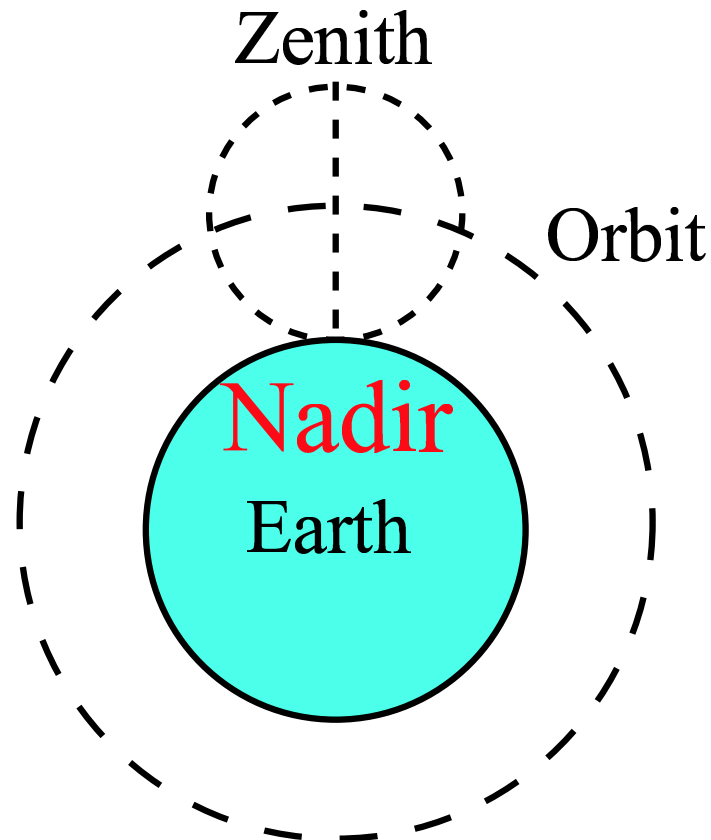
- Leading meteorological observations (MetOp and COSMOSkyMed)
- Studying the Earth gravitational field and the geoid morphology (GOCE)
- Building **extremely detailed maps** (GLOBCOVER)





# *Nadir observations*

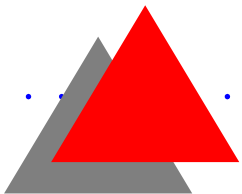
**Nadir** is the point on the ground below the satellite



# Nadir satellites

They are equipped with a **fixed instrumentation** nadir-oriented (pointing downwards)

- **global coverage** of the planet
  - **low-altitude transits**
- ⇒ **neat and detailed images**



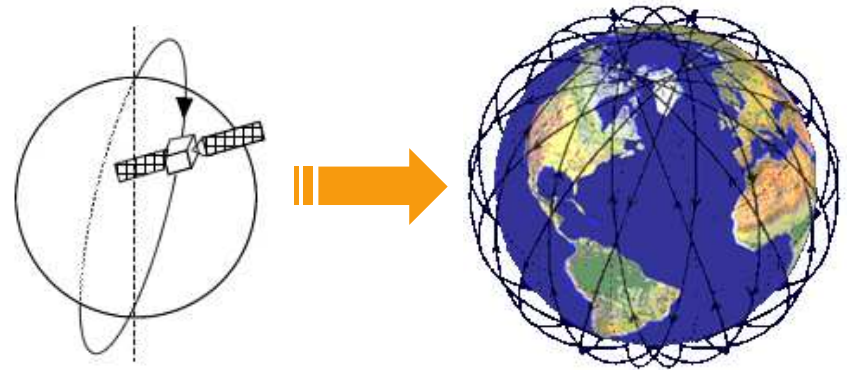


# POE satellites

**POES:** Polar Operational Environmental Satellites

The orbit is *quasi-polar*

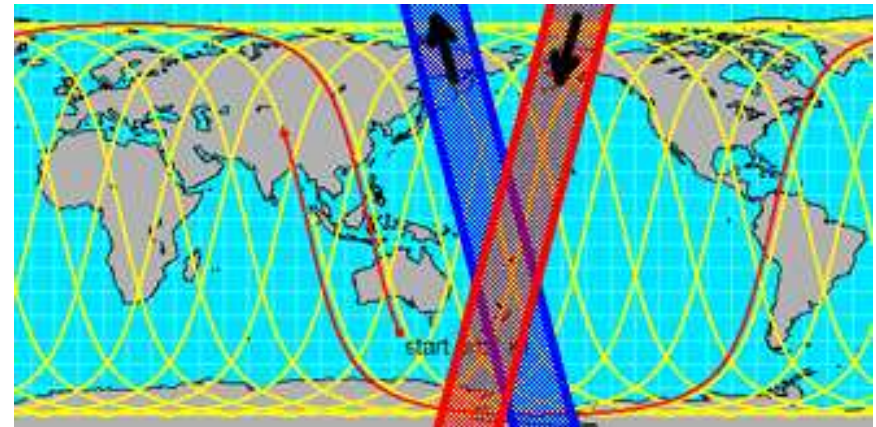
Since the Earth rotates, the tracks of the transits cross each other forming a **grid**



The satellite transits in two directions

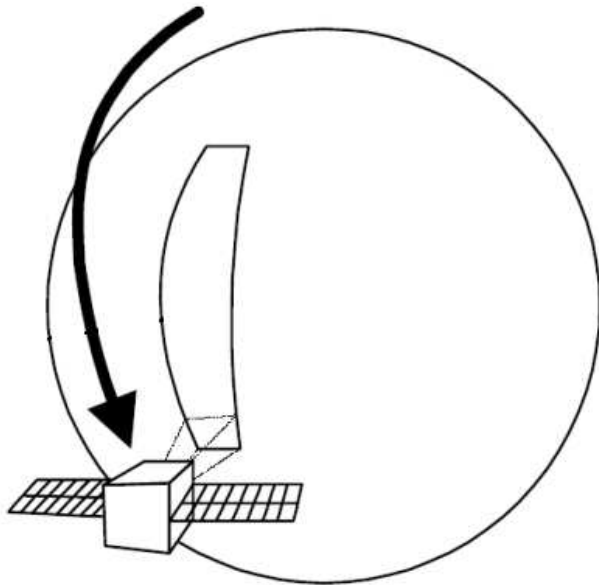
● **descending**

● **ascending**

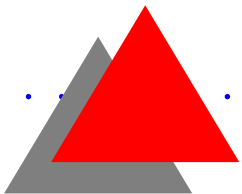
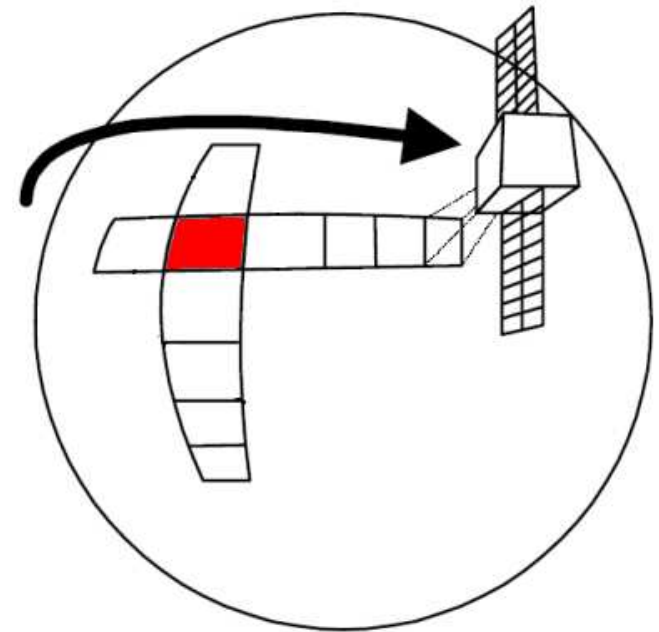


# Definitions (1)

Each satellite transit determines a strip named **swath**



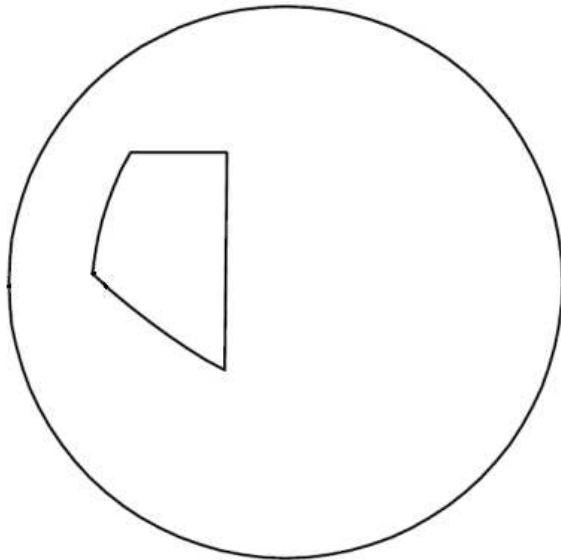
Due to the intersections, each swath is divided into areas named **segments**



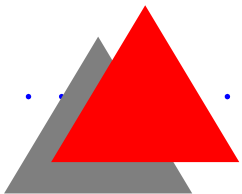
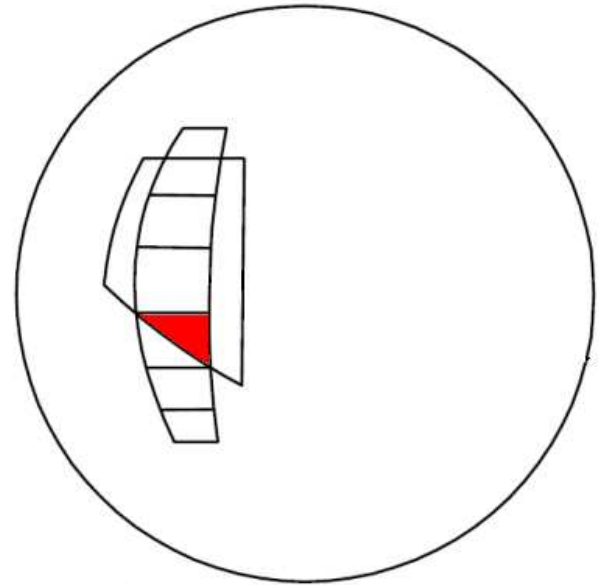


# Definitions (2)

Each portion of land which must be acquired is named **target**.



The intersection between a segment and a target is named **shard**.



# The Swath Segment Selection Problem

Define for each shard  $(i, j)$

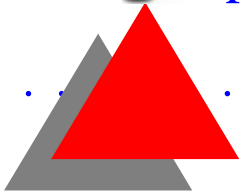
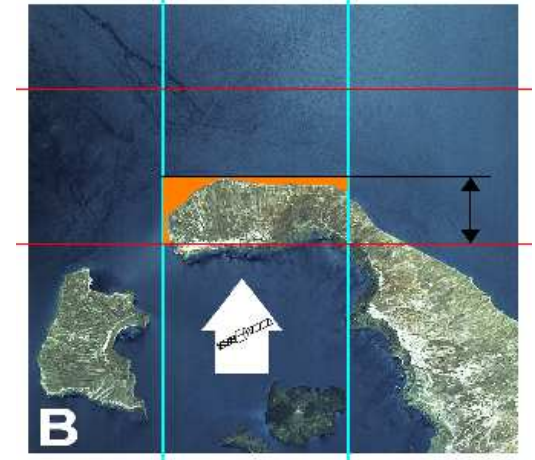
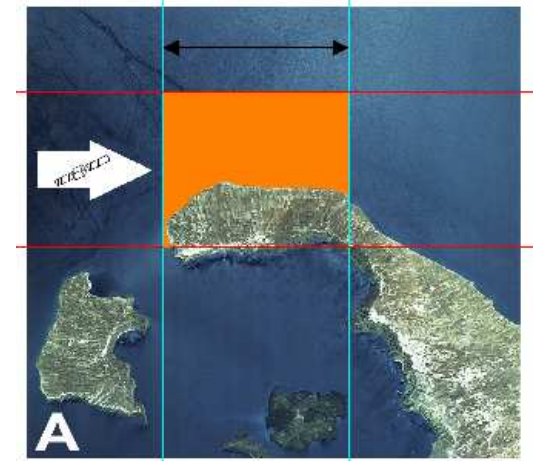
- a **reward**  $r_{ij}$
- a **horizontal**  $a_{ij}^{(h)}$  and a **vertical**  $a_{ij}^{(v)}$  area

Objective function

- Acquire **the most rewarding** subset of images

Constraints

- **Downlink capacities**  $d_i^{(h)}$  and  $d_j^{(v)}$
- Acquire each shard at most once





# References

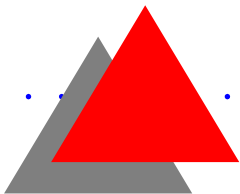
There is **almost no literature** on the subject.

- Greedy algorithm

Muraoka H., Cohen R.H., Ohno T., Doi N.  
*ASTER observation scheduling algorithm*  
SpaceOps 98, Tokio 1998

- Branch-and-bound based on linear relaxation, solved by max-flow (requires  $a_{ij}^{(h)} = a_{ij}^{(v)} \propto r_{ij}!$ )

Knight R., Smith B.  
*Optimal nadir observation scheduling*  
Fourth International Workshop on Planning and Scheduling for Space, Darmstadt 2004



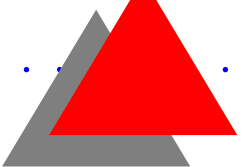


# An IP formulation for the SSSP

$$\begin{aligned} \max \quad & z = \sum_{i=1}^m \sum_{j=1}^n r_{ij} \left( x_{ij}^{(h)} + x_{ij}^{(v)} \right) \\ & \sum_{j=1}^n a_{ij}^{(h)} x_{ij}^{(h)} \leq d_i^{(h)} \quad i = 1, \dots, m \\ & \sum_{i=1}^m a_{ij}^{(v)} x_{ij}^{(v)} \leq d_j^{(v)} \quad j = 1, \dots, n \\ & x_{ij}^{(h)} + x_{ij}^{(v)} \leq 1 \quad i = 1, \dots, m \quad j = 1, \dots, n \\ & x_{ij}^{(h)}, x_{ij}^{(v)} \in \{0, 1\} \quad i = 1, \dots, m \quad j = 1, \dots, n \end{aligned}$$

●  $x_{ij}^{(h)} = 1$  if shard  $(i, j)$  is acquired along a **horizontal transit**

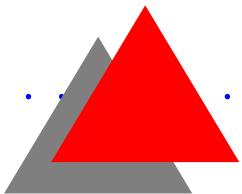
●  $x_{ij}^{(v)} = 1$  if shard  $(i, j)$  is acquired along a **vertical transit**





# Lagrangian relaxation

$$\begin{aligned} \max \quad & z = \sum_{i=1}^m \sum_{j=1}^n r_{ij} \left( x_{ij}^{(h)} + x_{ij}^{(v)} \right) \\ & \sum_{j=1}^n a_{ij}^{(h)} x_{ij}^{(h)} \leq d_i^{(h)} \quad i = 1, \dots, m \\ & \sum_{i=1}^m a_{ij}^{(v)} x_{ij}^{(v)} \leq d_j^{(v)} \quad j = 1, \dots, n \\ & x_{ij}^{(h)} + x_{ij}^{(v)} \leq 1 \quad i = 1, \dots, m \quad j = 1, \dots, n \\ & x_{ij}^{(h)}, x_{ij}^{(v)} \in \{0, 1\} \quad i = 1, \dots, m \quad j = 1, \dots, n \end{aligned}$$





# Lagrangian relaxation

$$\max z = \sum_{i=1}^m \sum_{j=1}^n r_{ij} \left( x_{ij}^{(h)} + x_{ij}^{(v)} \right) - \sum_{i=1}^m \sum_{j=1}^n \lambda_{ij} \left( x_{ij}^{(h)} + x_{ij}^{(v)} - 1 \right)$$

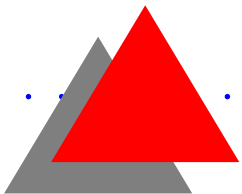
$$\sum_{j=1}^n a_{ij}^{(h)} x_{ij}^{(h)} \leq d_i^{(h)} \quad i = 1, \dots, m$$

$$\sum_{i=1}^m a_{ij}^{(v)} x_{ij}^{(v)} \leq d_j^{(v)} \quad j = 1, \dots, n$$

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$$x_{ij}^{(h)} + x_{ij}^{(v)} \leq 1 \quad i = 1, \dots, m \quad j = 1, \dots, n$$

$$x_{ij}^{(h)}, x_{ij}^{(v)} \in \{0, 1\} \quad i = 1, \dots, m \quad j = 1, \dots, n$$

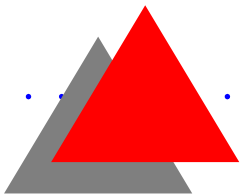






# The Lagrangean subproblem (1)

$$\begin{aligned} LR : \max z &= \sum_{i=1}^m \left\{ \begin{array}{l} \max \quad \xi_i^{(\lambda)} = \sum_{j=1}^n r_{ij}^{(\lambda)} x_{ij}^{(h)} \\ \text{s.t.} \quad \sum_{j=1}^n a_{ij}^{(h)} x_{ij}^{(h)} \leq d_i^{(h)} \\ x_{ij}^{(h)} \in \{0, 1\} \quad j = 1, \dots, n \end{array} \right. + \\ &+ \sum_{j=1}^n \left\{ \begin{array}{l} \max \quad \phi_j^{(\lambda)} = \sum_{i=1}^m r_{ij}^{(\lambda)} x_{ij}^{(v)} \\ \text{s.t.} \quad \sum_{i=1}^m a_{ij}^{(v)} x_{ij}^{(v)} \leq d_j^{(v)} \\ x_{ij}^{(v)} \in \{0, 1\} \quad i = 1, \dots, m \end{array} \right. + \\ &+ \sum_{i=1}^m \sum_{j=1}^n \lambda_{ij} \end{aligned} \quad \text{where } r_{ij}^{(\lambda)} = r_{ij} - \lambda_{ij}$$



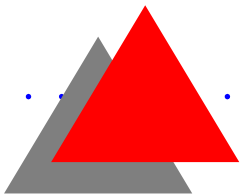


# The Lagrangean subproblem (2)

$$LR : \max z = \sum_{i=1}^m \xi_i^{*(\lambda)} + \sum_{j=1}^n \phi_j^{*(\lambda)} + \sum_{i=1}^m \sum_{j=1}^n \lambda_{ij}$$

where

- $\xi_i^{*(\lambda)}$ : optimum of a **knapsack problem** on **horizontal swath  $i$**
- $\phi_j^{*(\lambda)}$ : optimum of a **knapsack problem** for **vertical swath  $j$**
- $\sum_{i=1}^m \sum_{j=1}^n \lambda_{ij}$  is **constant** (for a given multiplier matrix  $\lambda$ )





# Lagrangean heuristic (1)

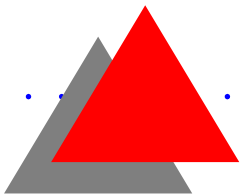
- **Horizontal heuristic:**

1. solve the “horizontal” knapsack problems to get  $x_{ij}^{(h)}$
2. set  $a_{ij}^{(v)} = +\infty$  to remove all shards acquired ( $x_{ij}^{(h)} = 1$ )
3. solve the “vertical” knapsack problems to get  $x_{ij}^{(v)}$

- **Vertical heuristic:**

1. solve the “vertical” knapsack problems to get  $x_{ij}^{(v)}$
2. set  $a_{ij}^{(h)} = +\infty$  to remove all shards acquired ( $x_{ij}^{(v)} = 1$ )
3. solve the “horizontal” knapsack problems to get  $x_{ij}^{(h)}$

- Choose the best among the two solutions



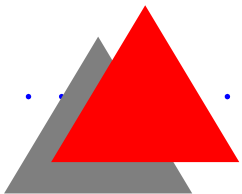


# Lagrangean heuristic (2)

If  $\lambda \neq 0$

- fix the shards acquired once in the Lagrangean solution
  - reduce the downlink capacities
  - solve the knapsack sub-problems considering the shards acquired twice and those not acquired
- use Lagrangean rewards  $r_{ij}^{(\lambda)}$  instead of  $r_{ij}$

Real-valued rewards  $\Rightarrow$  Pisinger-Ceselli code





# Subgradient ascent

Given a heuristic solution  $x_{LB}$  of reward  $z_{LB}$

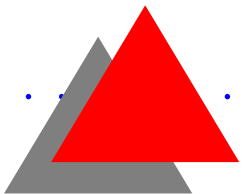
1. Solve the Lagrangean subproblem  $\Rightarrow x_{UB}$  (reward  $z_{UB}$ )
2. Compute the current violation of the relaxed constraints

$$s = x_{UB}^{(h)} + x_{UB}^{(v)} - 1$$

3. Compute the update step  $T = t \frac{z_{UB} - LB}{\|s\|^2}$

4. Update the multipliers

$$\lambda'_{ij} = \begin{cases} 0 & \text{if } \lambda_{ij} + T s_{ij} < 0 \\ \lambda_{ij} + T s_{ij} & \text{if } 0 \leq \lambda_{ij} + T s_{ij} \leq r_{ij} \\ r_{ij} & \text{if } \lambda_{ij} + T s_{ij} > r_{ij} \end{cases}$$





# The branching strategy

The **branching shard**  $(i, j)$  is the one with **maximum**  $\lambda_{ij}$

(a) **acquired in both directions** in the Lagrangean solution

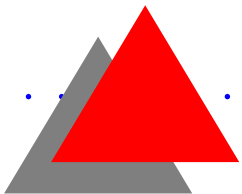
$$(x_{LB_{ij}}^{(h)} = x_{LB_{ij}}^{(v)} = 1)$$

(b) **not acquired** in the Lagrangean solution  $(x_{LB_{ij}}^{(h)} = x_{LB_{ij}}^{(v)} = 0)$

Three subproblems

1. **Horizontal acquisition**: set  $x_{ij}^{(h)} = 1$  and  $x_{ij}^{(v)} = 0$
2. **Vertical acquisition**: set  $x_{ij}^{(h)} = 0$  and  $x_{ij}^{(v)} = 1$
3. **No acquisition**: set  $x_{ij}^{(h)} = 0$  and  $x_{ij}^{(v)} = 0$

The visit strategy is **best-bound-first**





# The benchmark problems

Two size classes

- 10 small sizes (100 to 10 000 shards)
- 4 large sizes (from 40 000 to 250 000 shards)

14 sizes

Three downlink capacities

- 20% or 30% or 40% of the total reward

3 capacities

Two ranges for rewards and areas:

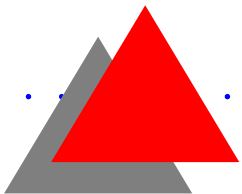
- small (S): values in [1; 100]
- large (L): values in [51; 100]

8 areas  
and rewards

$(a_{ij}^{(h)} = a_{ij}^{(v)} \text{ or not})$

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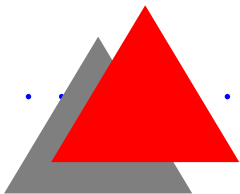
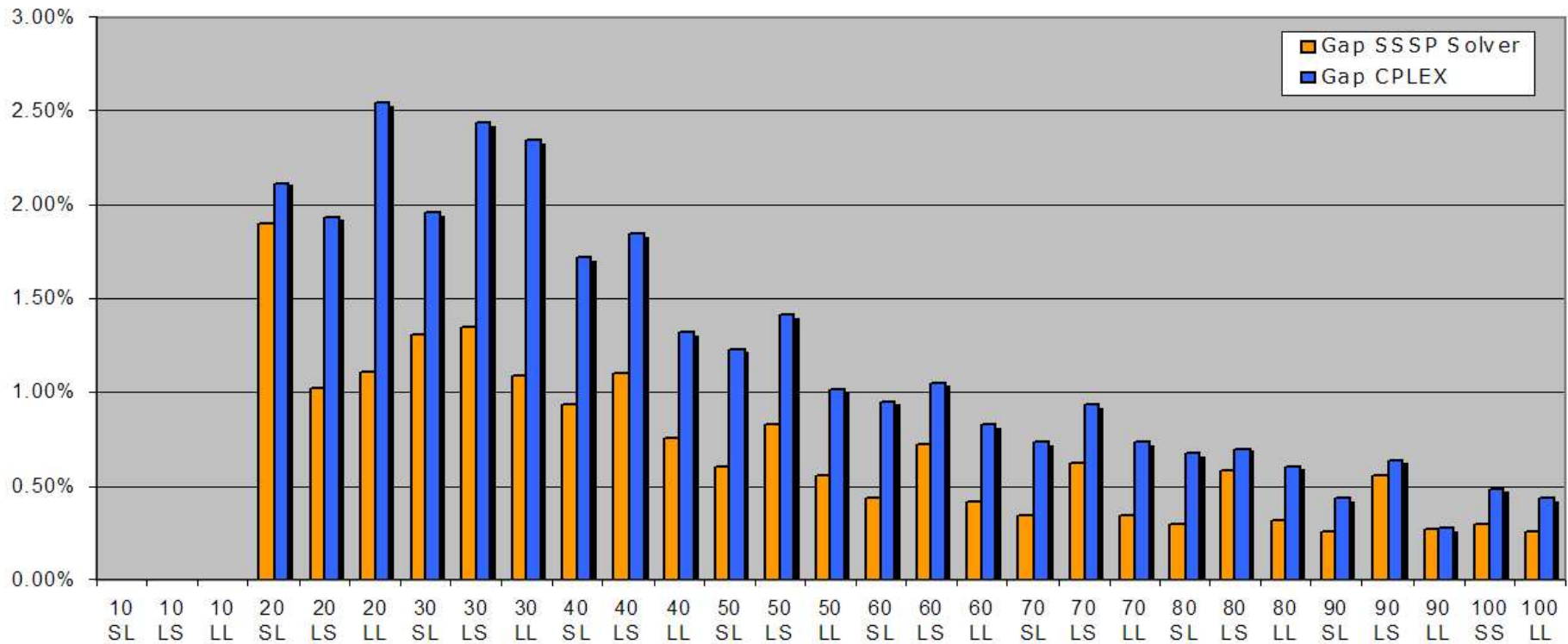
336  
instances





# Experimental results (1)

Gap achieved in **30 minutes** by CPLEX 8.0 and SSSP solver on small instances

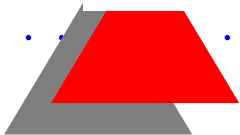
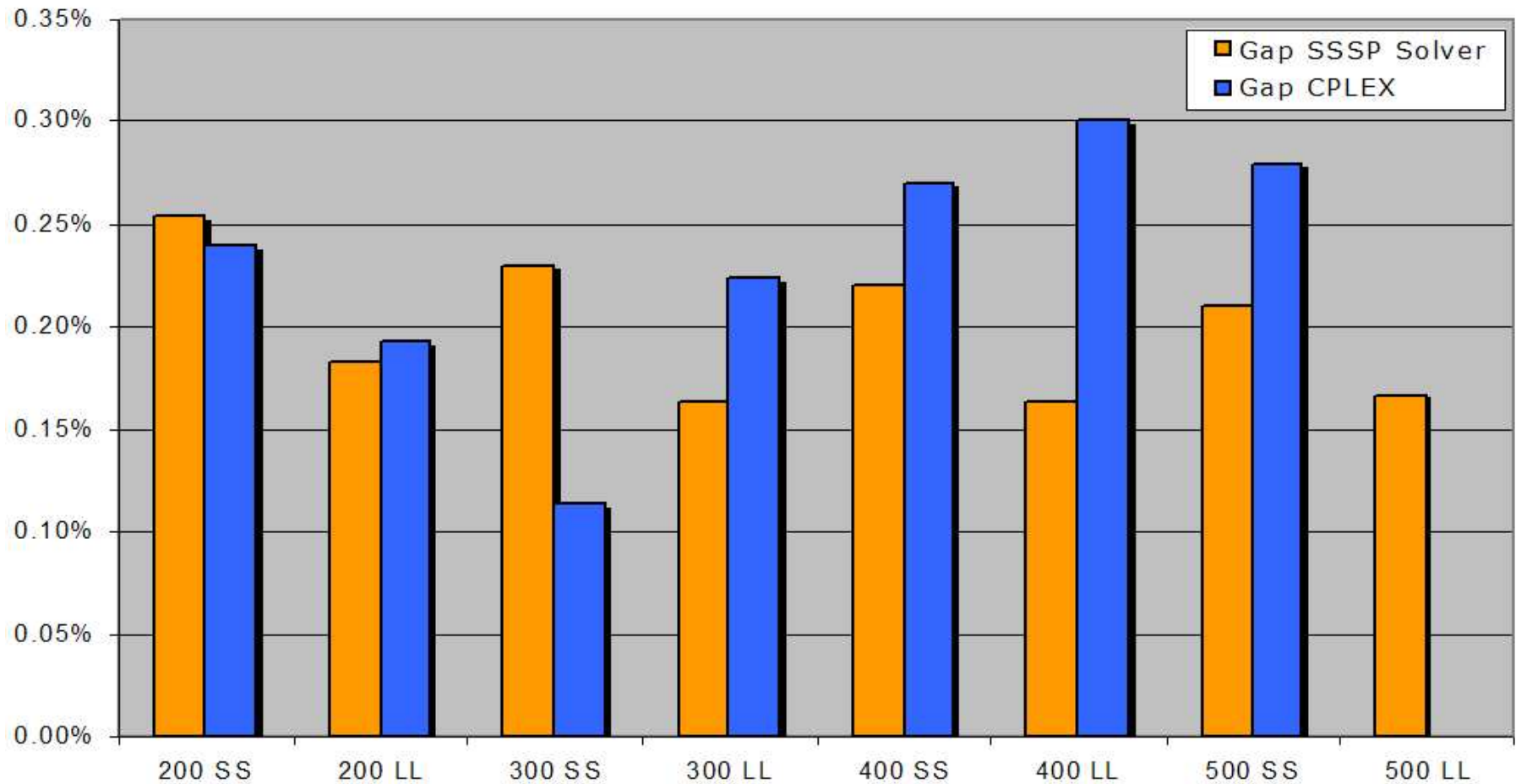






# Experimental results (2)

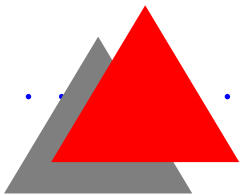
Gap achieved **at the root node** by CPLEX 8.0 and SSSP solver on large instances





# *Experimental results (3)*

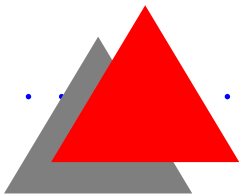
- **SSSP solver**
  - required from 1 to 6 minutes on the SS instances
  - was stopped after 30 minutes on the LL instances
- **CPLEX 8.0**
  - always required more than 30 minutes
  - could not solve the root node in 60 minutes on the 500 LL instances





# Conclusions

- The problem is hard, even for rather small sizes
- **Hardness increases from SS to SL, to LS and to LL instances** (smaller range)
- The algorithm yields **tighter bounds than CPLEX** (both **better heuristic solutions** and **better upper bounds**)
- The **Lagrangian relaxation is tighter than the linear one** (though enhanced by general-purpose cuts)
- The **branching proposed improves the bounds**, while CPLEX branching most of the time does not





# *More on this...*

...can be found in:

R. Cordone, F. Gandellini, G. Righini

*Solving the swath segment selection problem through  
Lagrangian relaxation*

Computers and O.R., to appear.

