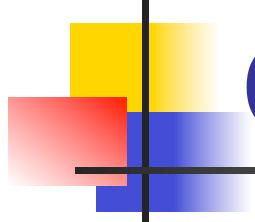


# Scheduling With Constraint Programming

Pascal Van Hentenryck

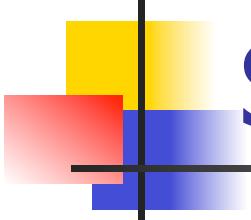
Brown University



# Outline

---

- Motivation
- Jobshop Scheduling
- Asymmetric TSP with Time Windows
- Cumulative Scheduling

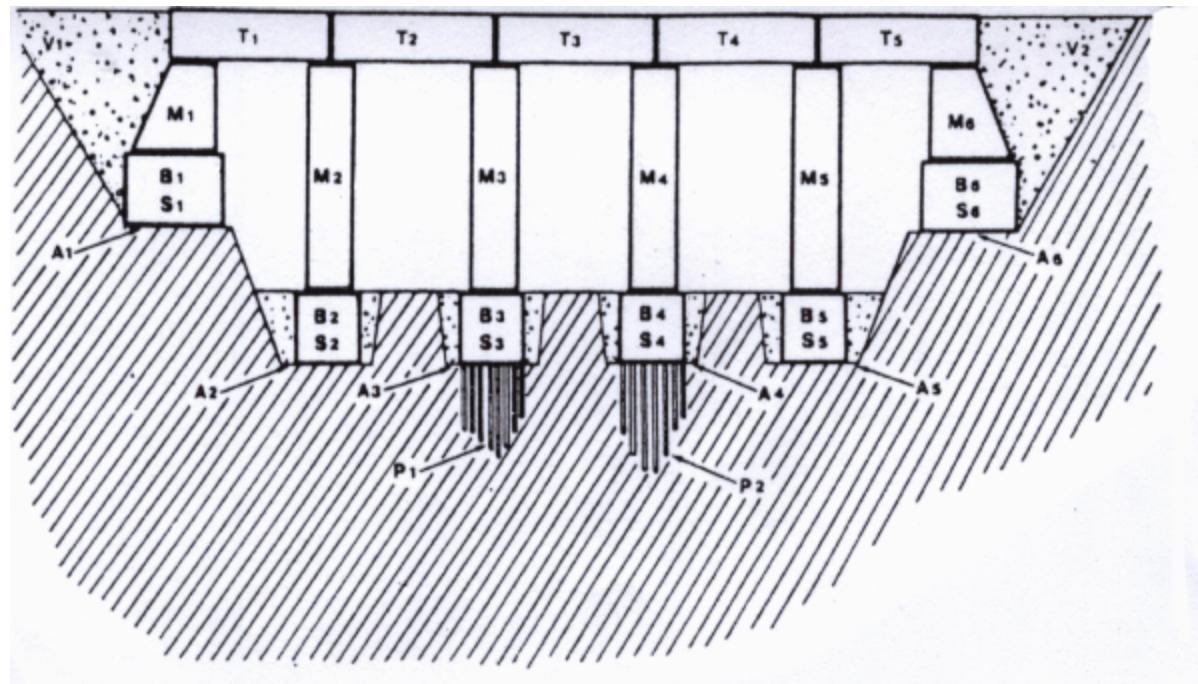


# Scheduling

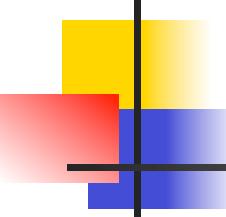
---

- Very successful application area for CP
- Minimize project duration subject
  - Precedence constraints
  - Disjunctive constraints: no two tasks scheduled on the same machine cannot overlap in time

# Scheduling



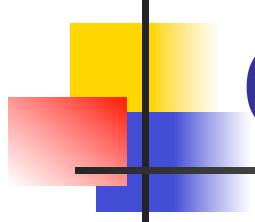
Pascal Van Hentenryck



# Vertical Extensions

---

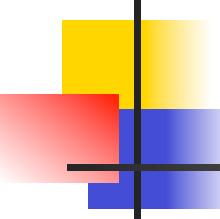
- Model-based computing
- Based on concepts of
  - activities,
  - resources
  - precedence constraints
  - ...
- Encapsulates variables and global constraints
- Support search procedures



# Outline

---

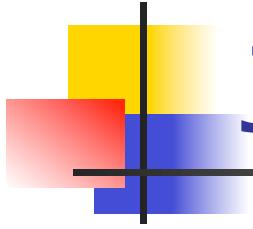
- Motivation
- Jobshop Scheduling
- Cumulative Scheduling



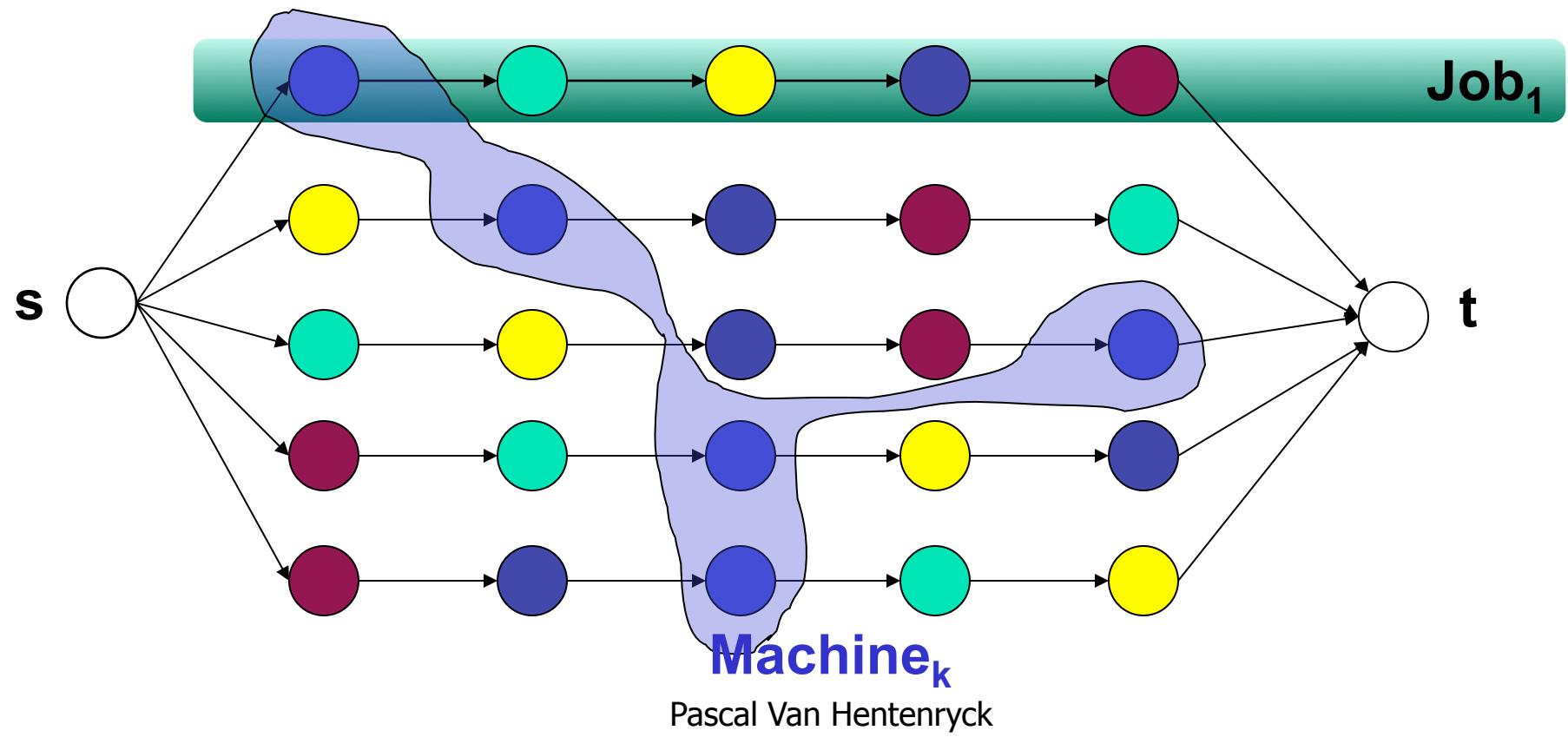
# Jobshop Scheduling

---

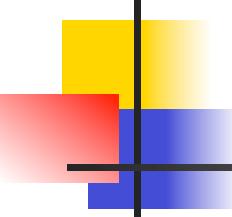
- Problem formulation
  - a set of tasks is given, e.g., 1..100
  - each task  $t$  has a duration  $d(t)$
  - each task  $t$  has a machine  $m(t)$  to execute
  - a set of precedence constraints  $(b,a)$ 
    - $a$  can only start when  $b$  is completed
- Goal
  - minimize the project completion time



# Jobshop Scheduling

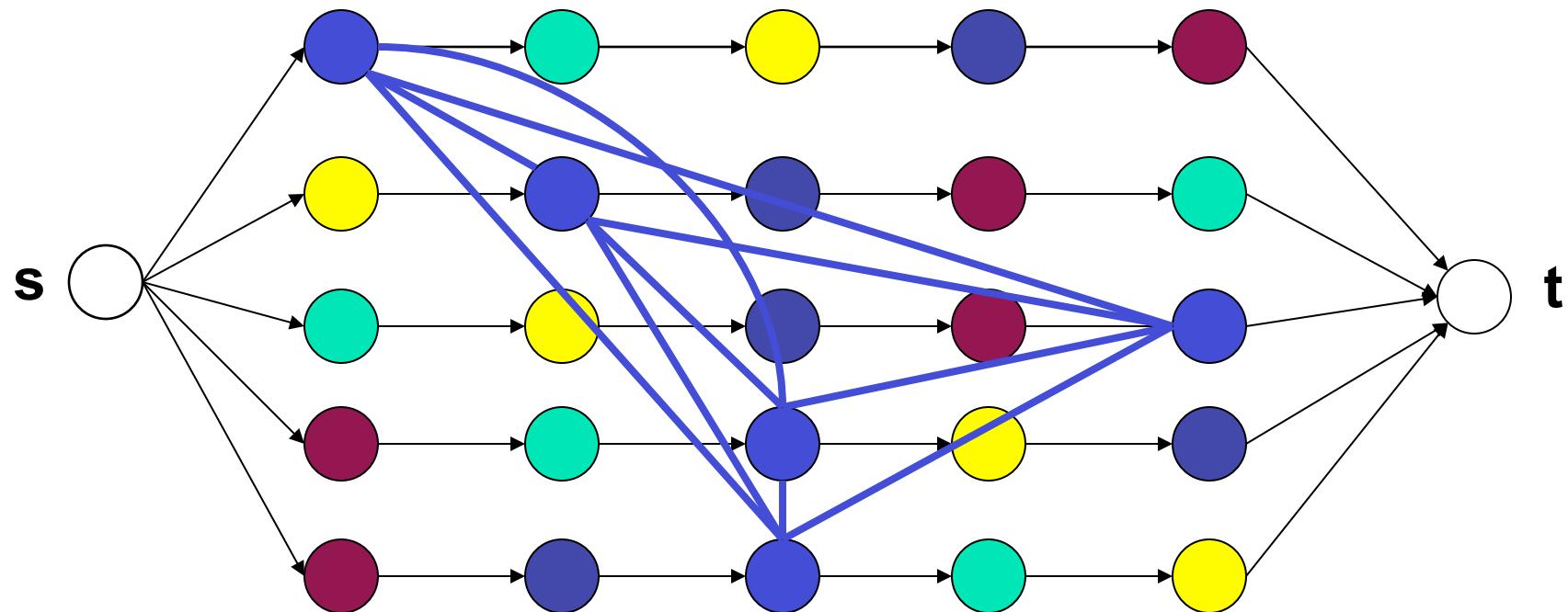


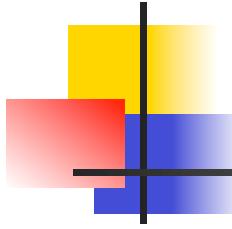
Pascal Van Hentenryck



# Jobshop Scheduling

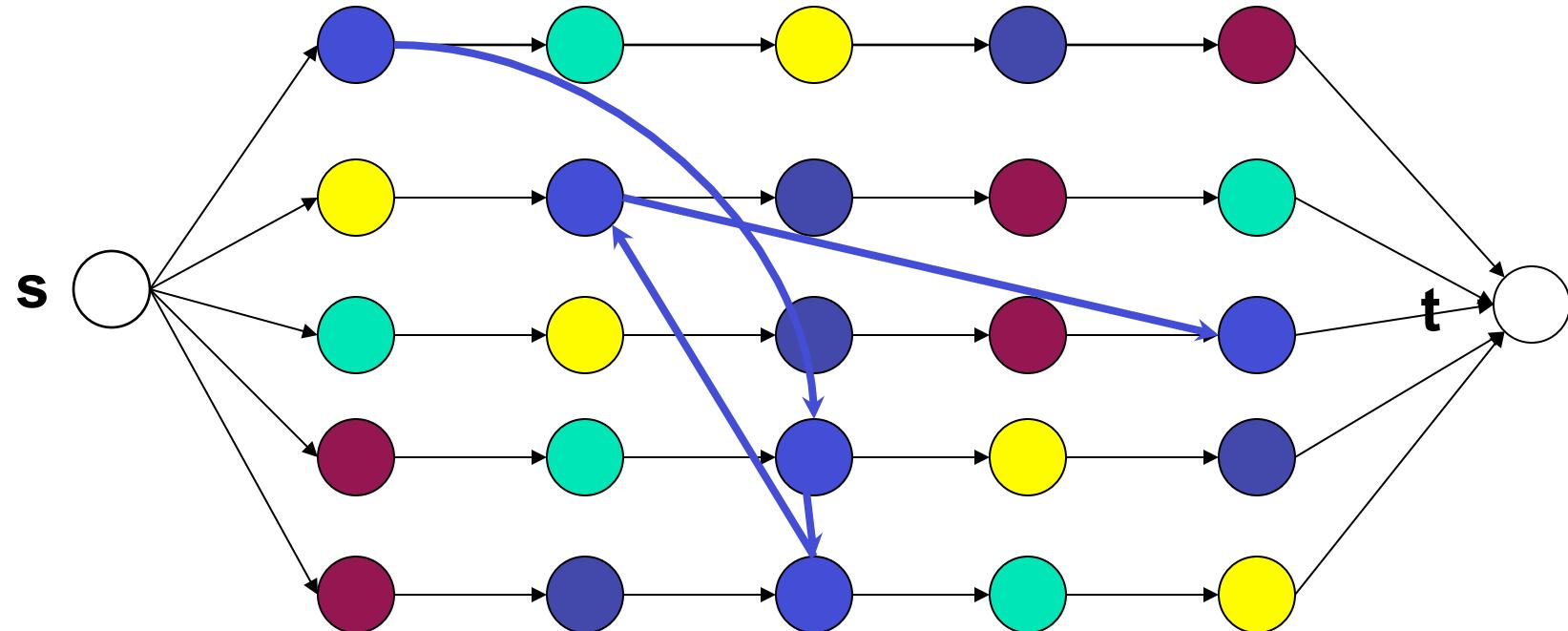
- A machine handle activities in sequence
  - Find a activity *ordering* on each machine

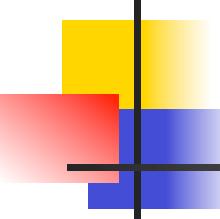




# Jobshop Scheduling

- Solution = a directed acyclic precedence graph





# Jobshop Scheduling

---

- Why is an ordering for each machine sufficient?
  - only precedence constraints left?
  - **easy to solve in polynomial time**
    - topological sorting (PERT)
    - transitive closure (Floyd-Warshall)

# Jobshop Scheduling Model

```
range Jobs = 0..nbJobs-1; range Tasks = 0..nbTasks-1; range Machines = Tasks;  
range Activities = 0..nbActivities+1;  
int duration[Jobs,Tasks];  
int machine[Jobs,Tasks];  
int horizon = sum(j in Jobs,t in Tasks) duration[j,t];
```

*Decision Variables*

```
Scheduler<CP> cp(horizon);  
Activity<CP> a[j in Jobs,t in Tasks](cp,duration[j,t]);  
Activity<CP> makespan(cp,0);
```

```
UnaryResource<CP> r[Machines](cp);
```

*Resources*

# Jobshop Scheduling Model

```
range Jobs = 0..nbJobs-1; range Tasks = 0..nbTasks-1; range Machines = Tasks;  
range Activities = 0..nbActivities+1;
```

```
int duration[Jobs,Tasks];
```

```
int machine[Jobs,Tasks];
```

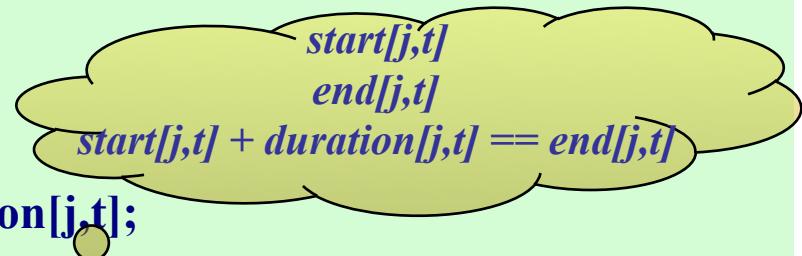
```
int horizon = sum(j in Jobs,t in Tasks) duration[j,t];
```

```
Scheduler<CP> cp(horizon);
```

```
Activity<CP> a[j in Jobs,t in Tasks](cp,duration[j,t]);
```

```
Activity<CP> makespan(cp,0);
```

```
UnaryResource<CP> r[Machines](cp);
```



# Jobshop Scheduling Model

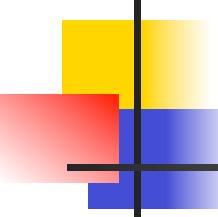
```
minimize<cp>
    makespan.end()
subject to {

    forall(j in Jobs, t in Tasks: t != Tasks.getUp())
        a[j,t].precedes(a[j,t+1]);
    forall(j in Jobs)
        a[j, Tasks.getUp()].precedes(makespan);

    forall(j in Jobs, t in Tasks)
        a[j,t].requires(r[machine[j,t]]);
}
```

*Precedence  
constraints*

*Resource  
constraints*



# Jobshop Scheduling Modeling

$t[1]$  precedes  $t[2]$ ;

...

$t[99]$  precedes  $t[100]$



$end[t[1]] \leq start[t[2]]$

**disjunctive**( $t[1], \dots, t[10]$ )

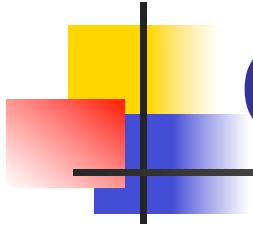
**disjunctive**( $t[11], \dots, t[20]$ )

...

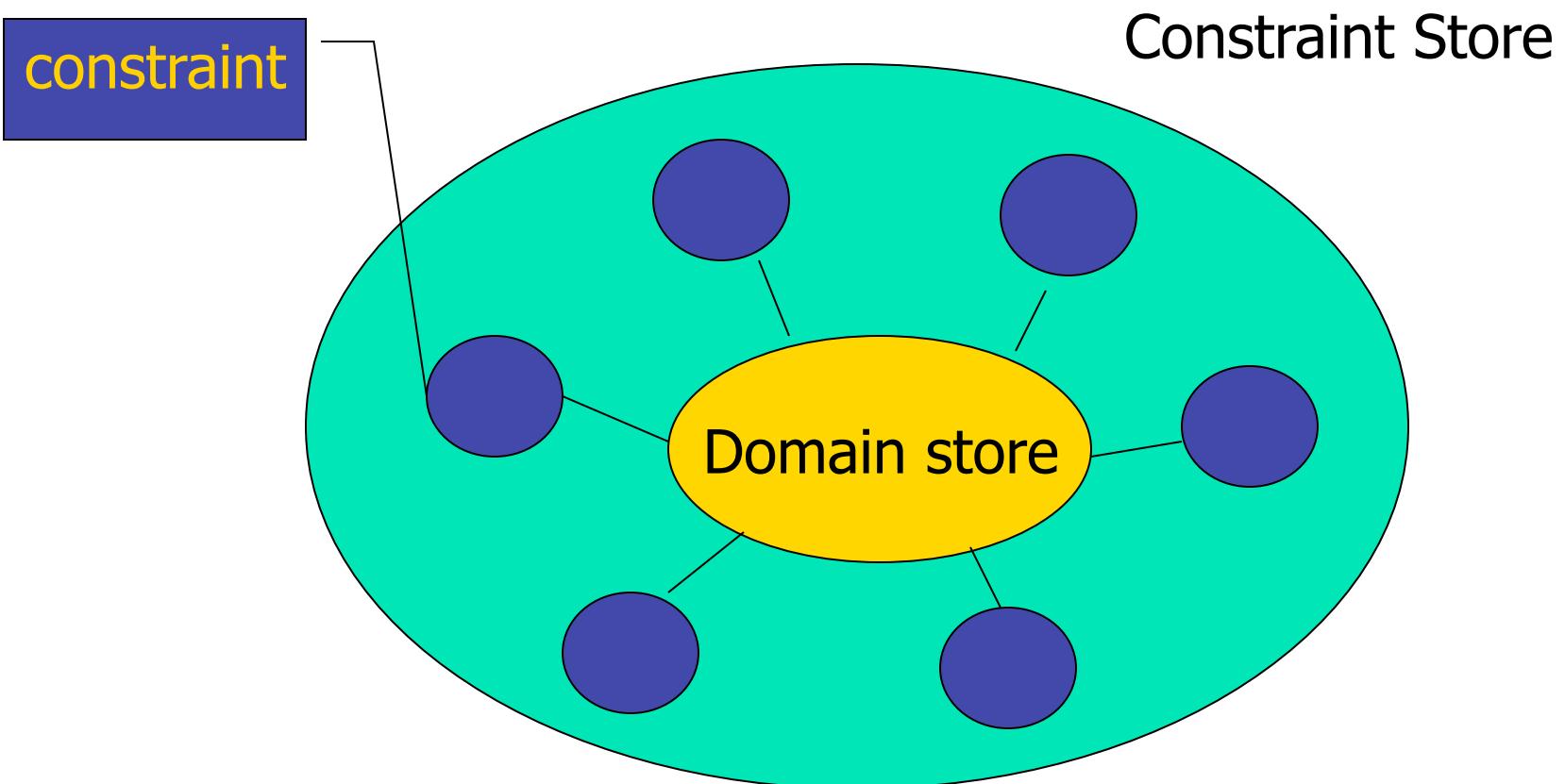
**disjunctive**( $t[91], \dots, t[100]$ )



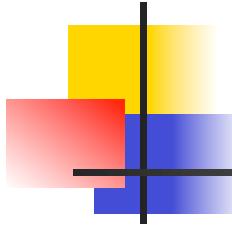
*global  
constraints*



# Computational Model



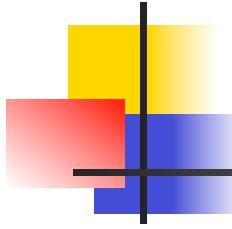
Pascal Van Hentenryck



# Disjunctive Scheduling

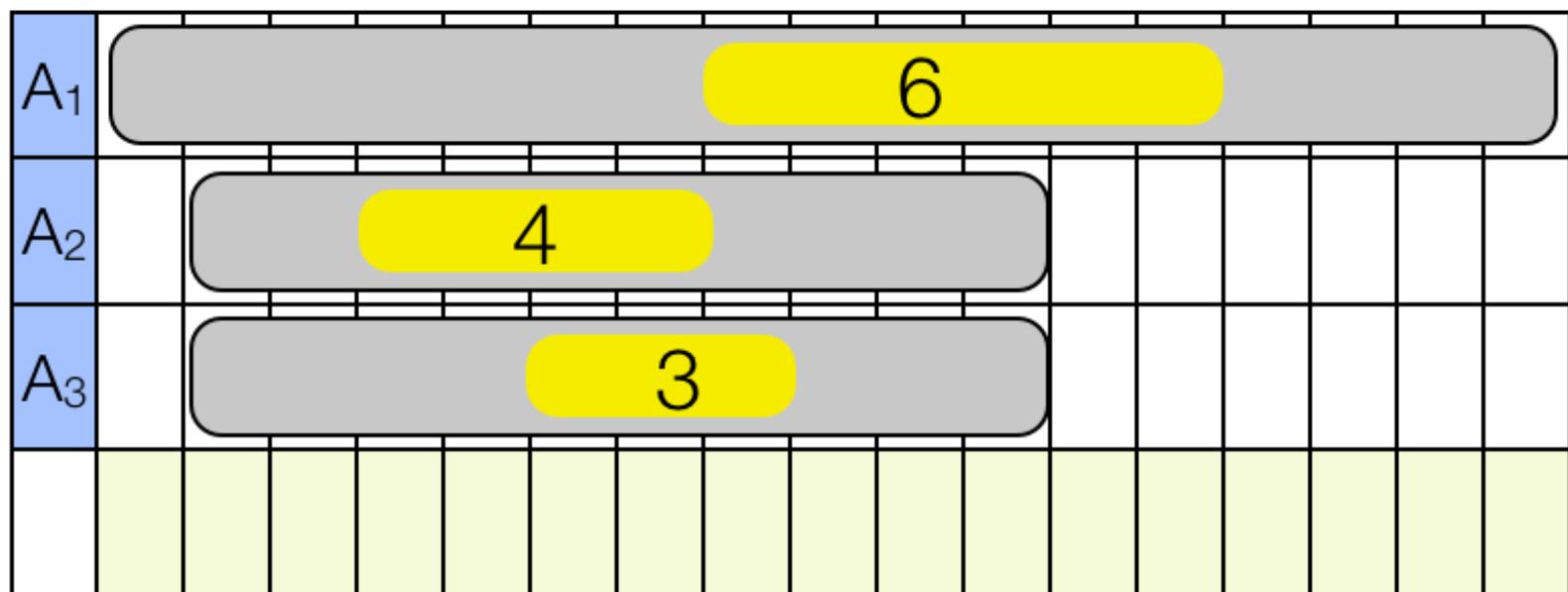
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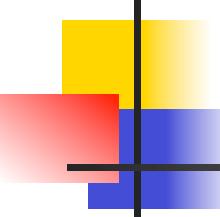
- A combinatorial constraint with each machine
  - all the tasks executing on the machine
- Two tasks
  - determining feasibility
  - reducing the domain of the variables
    - bound reduction



# Disjunctive Constraint

- ▶ One-Machine Feasibility

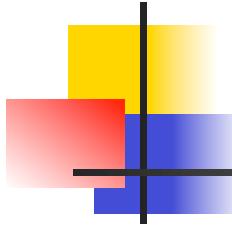




# Disjunctive Constraint

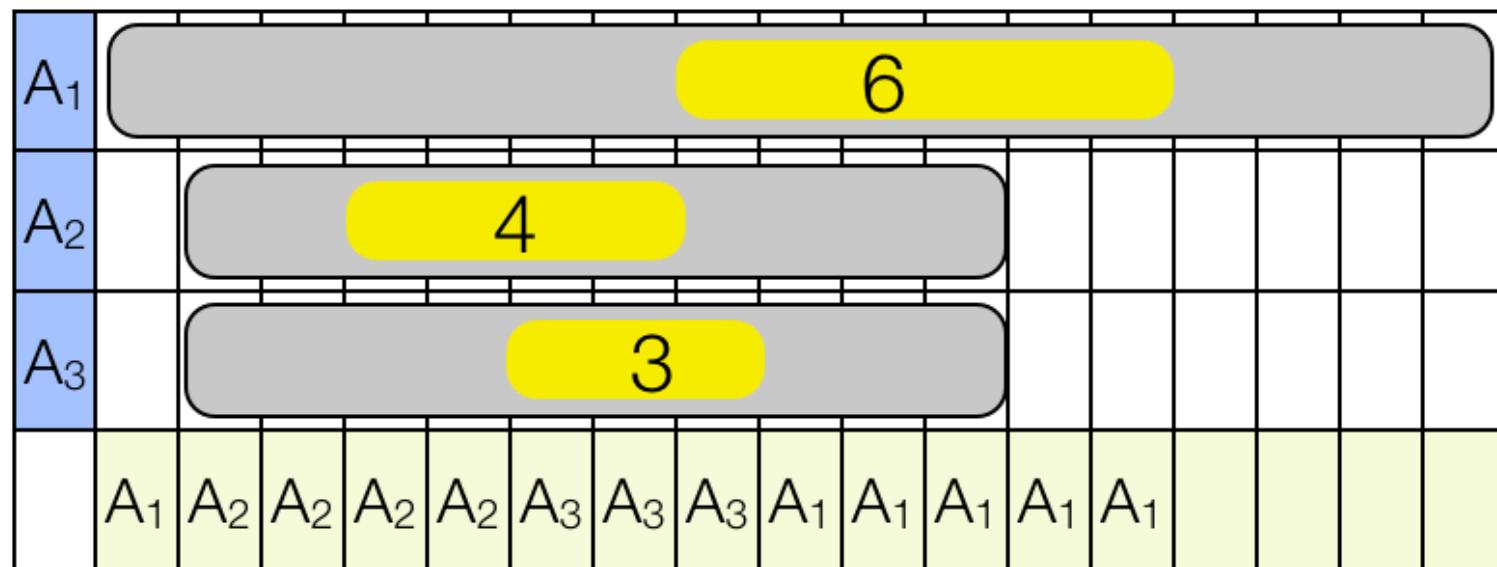
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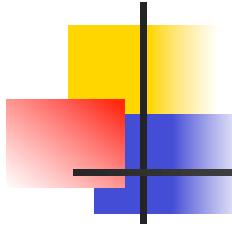
- ▶ Pruning: edge finder rules
  - select a set  $T$  of tasks and a task  $i$  such that  $i \notin T$
  - determine whether  $i$  must start after all tasks of  $T$ 
    - update its starting date:  $E(T) + D(T)$
  - determine whether  $i$  must finish before all tasks of  $T$ 
    - update its ending date:  $L(T) - D(T)$
- ▶ The edge-finder rules can be enforced in strongly polynomial time



# Disjunctive Constraint

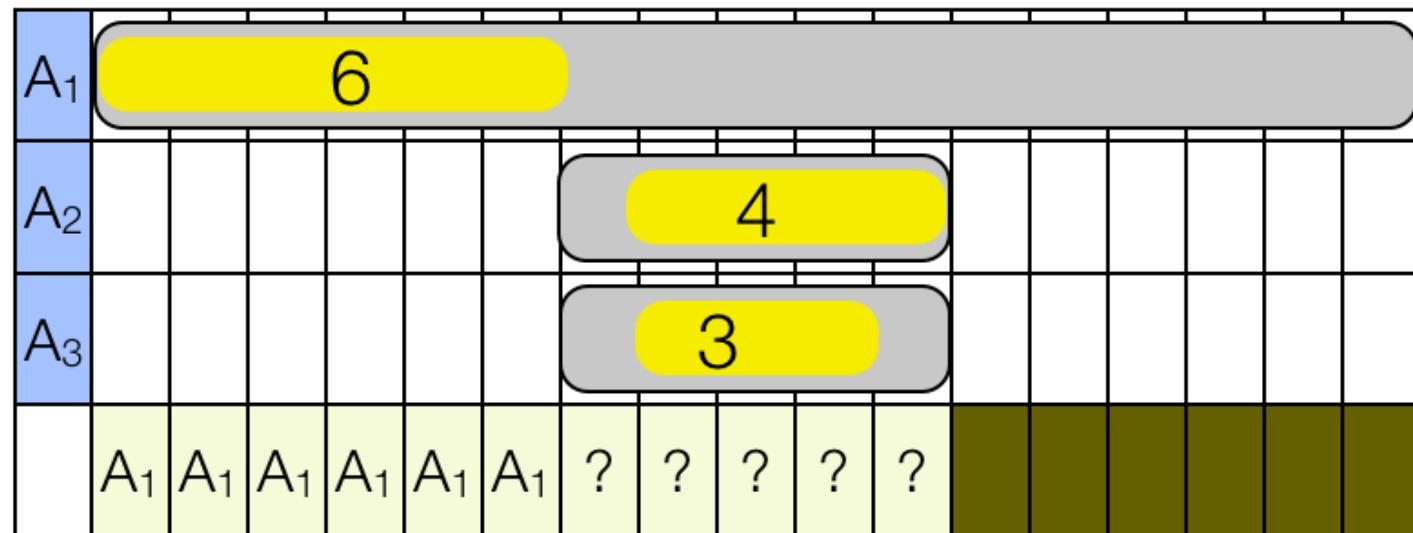
- ▶ Pruning: Can  $A_1$  start first?

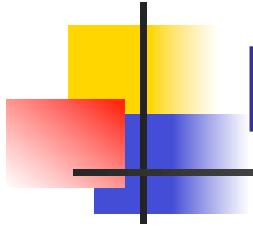




# Disjunctive Constraint

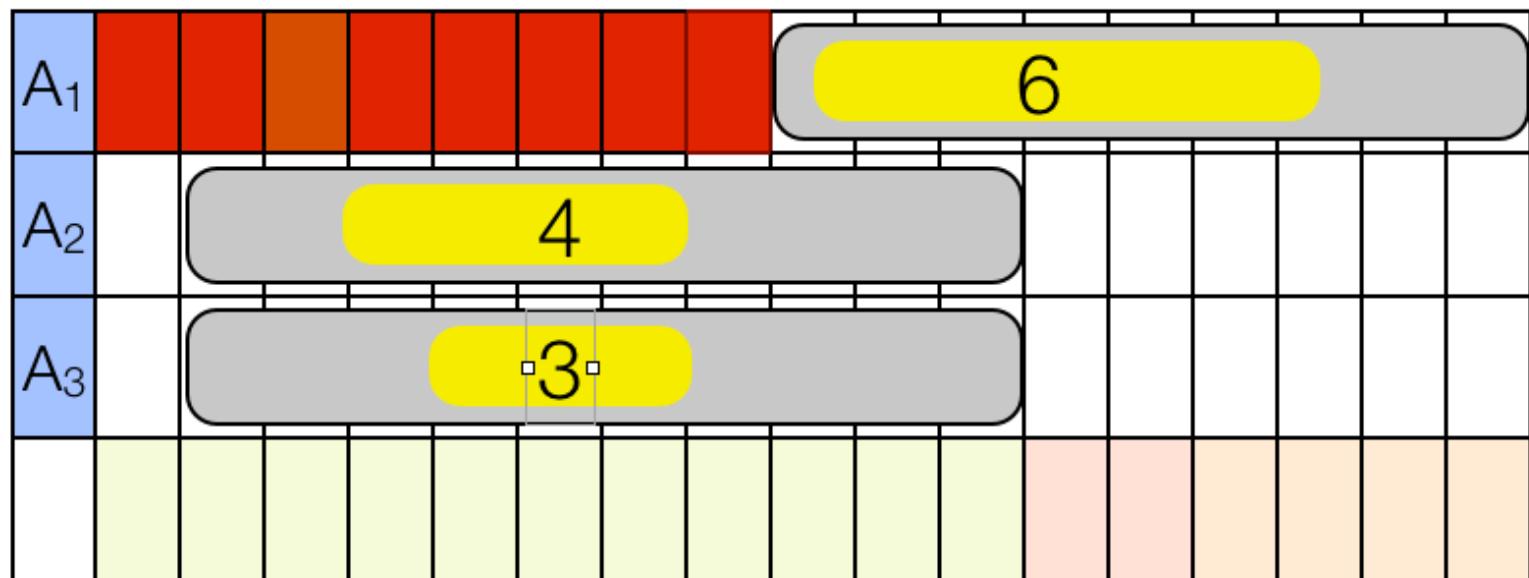
- ▶ Pruning: Can  $A_1$  start first?

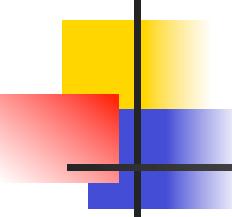




# Disjunctive Constraint

- ▶ Pruning:  $A_1$  must start after  $A_2$  and  $A_3$

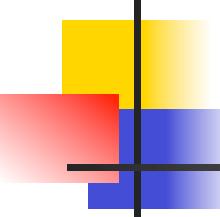




# Branching

---

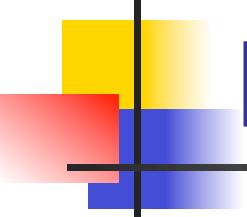
- How to branch?
  - choose a machine
  - choose a task to rank first on the machine
  - on backtracking, rank not first
- Which machine?
  - tightest machine
  - e.g., the least slack
- Which task?
  - a task that can be scheduled first
  - a task which is as tight as possible



# Search Strategies

---

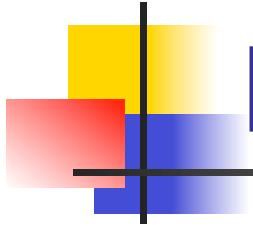
- Branching
  - specifies the tree to explore
  - does not specify how to explore it
- Search strategies
  - specifies how to explore the search tree
  - default: depth-first search
  - others:?



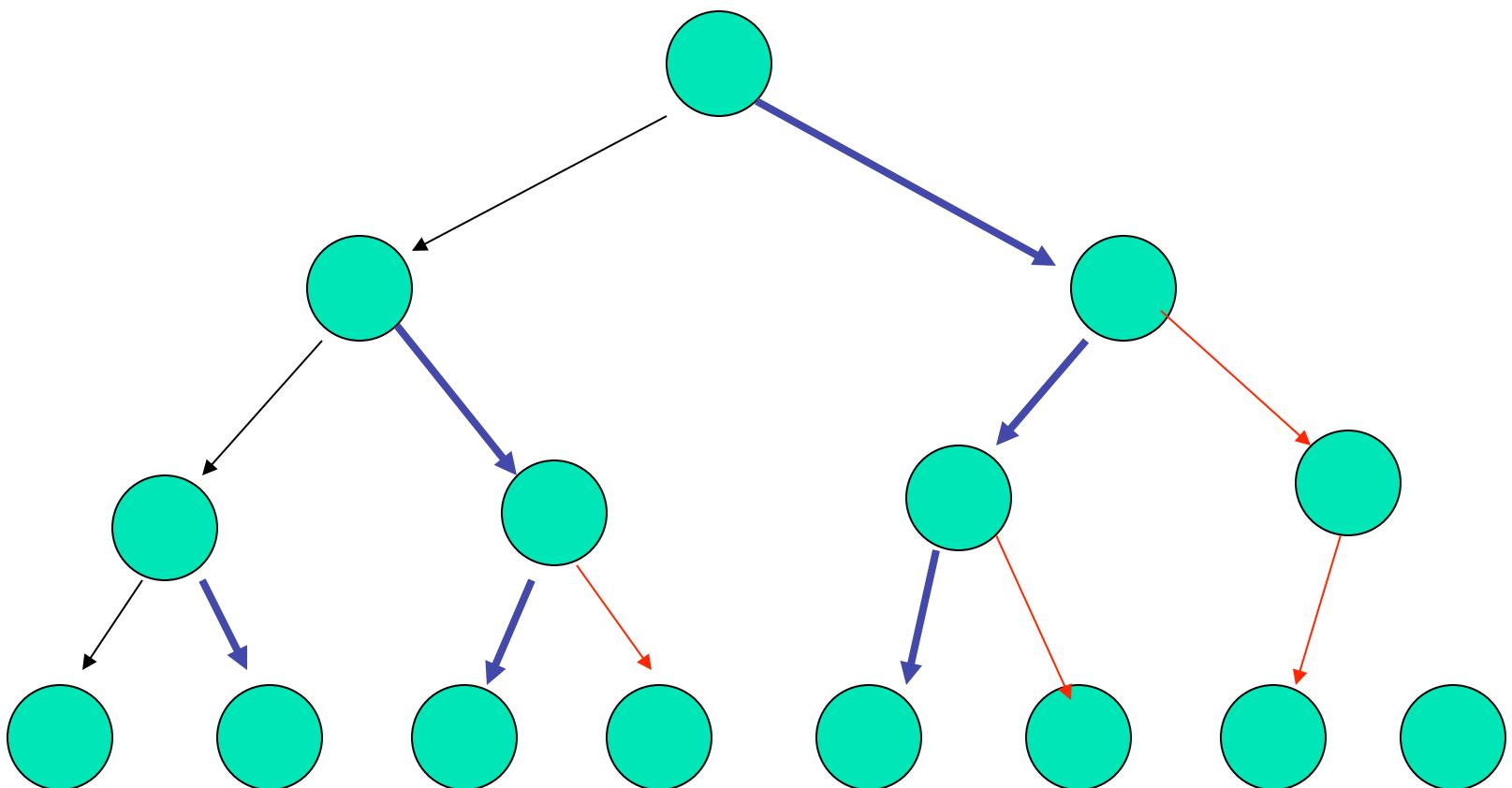
# Limited Discrepancy search

---

- Assume that we have a good heuristic which make few mistakes
- Follow the heuristic (left branch)
- Trust the heuristic less and less
  - assume that it makes 1 mistake
  - then assume that it makes 2 mistakes
- The search tree is explored in waves

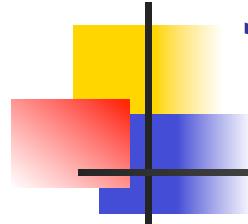


# Limited Discrepancy Search



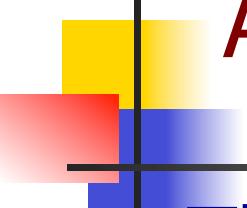
Pascal Van Hentenryck

# Jobshop Scheduling Search



```
cp.setSearchController(BDSController(cp, 3));
minimize<cp>
    makespan.end()
subject to {
    ...
} using {
    forall(m in Machines)  by (r[m].localSlack())
        r[m].rank();
    cp.post(makespan.end() == makespan.end().getMin());
}
```



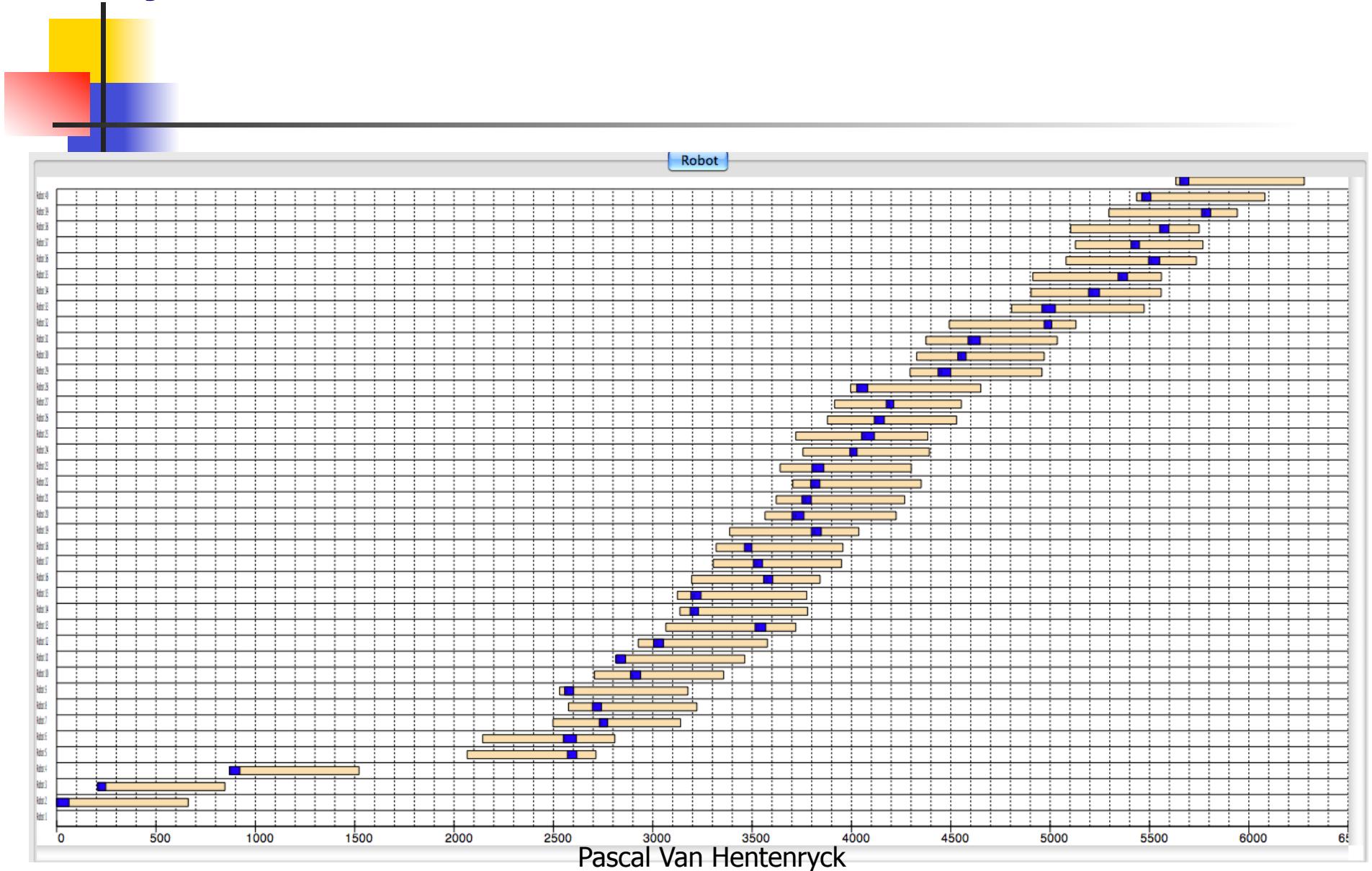


# Asymmetric TSP with Time Windows

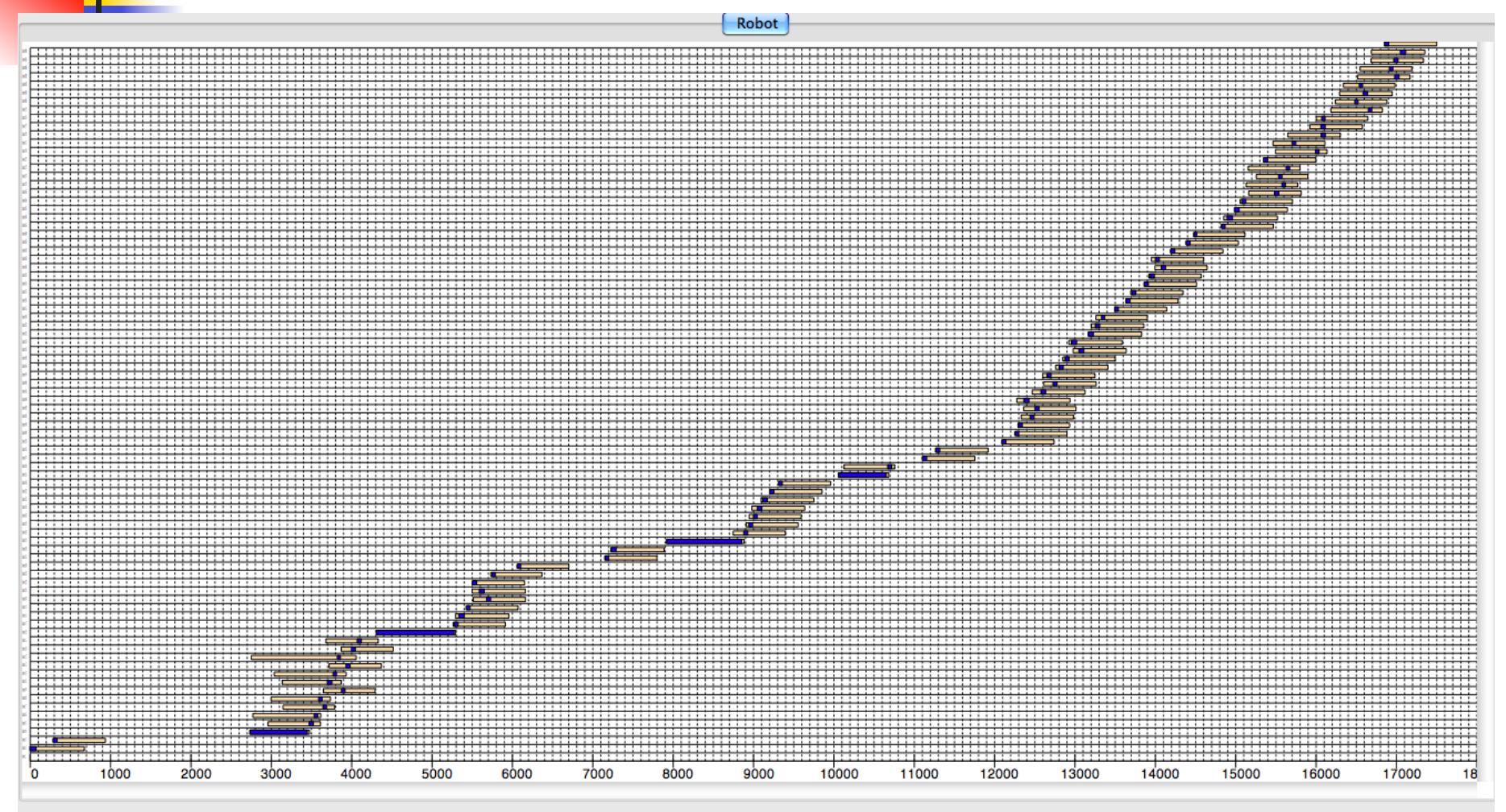
- The input: we are given
  - a set of locations to visit
  - a service time for each location
  - a time window when to serve a location
  - the (asymmetric) travel distance between locations
- the goal: find a hamiltonian path
  - satisfying the time windows
  - minimizing the travel distance

Tension

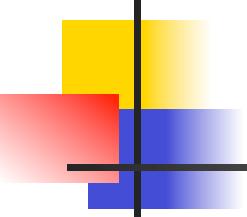
# Asymmetric TSP with Time Windows



# Asymmetric TSP with Time Windows

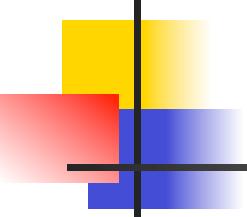


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# The CP Model

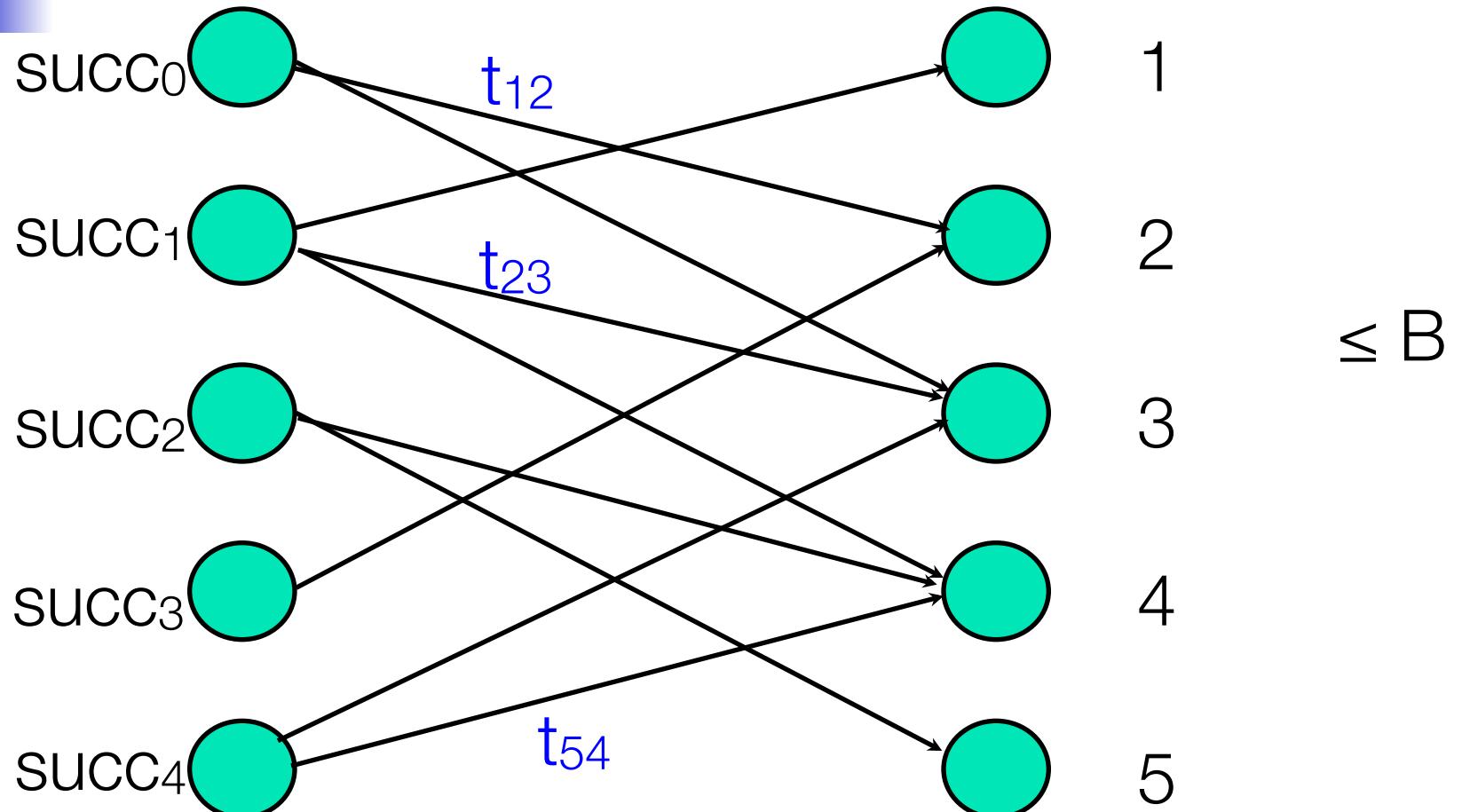
```
Scheduler<CP> cp(0,horizon);
Activity<CP> act[i in Activities](cp,service[i],i);
UnaryResource<CP> vehicle(cp,transitionTimes);
minimize<cp>
    vehicle.getSumTransitionTimes()
subject to
    forall(i in Activities) {
        cp.post(act[i].start() >= ws[i]);
        cp.post(act[i].start() <= we[i]);
        act[i].requires(vehicle);
    }
using {
    vehicle.sequenceForward();
    forall(i in Activities) label(act[i].start());
}
```

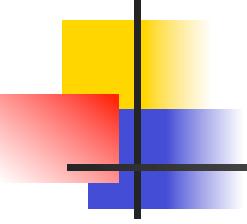


# Dual Modelling

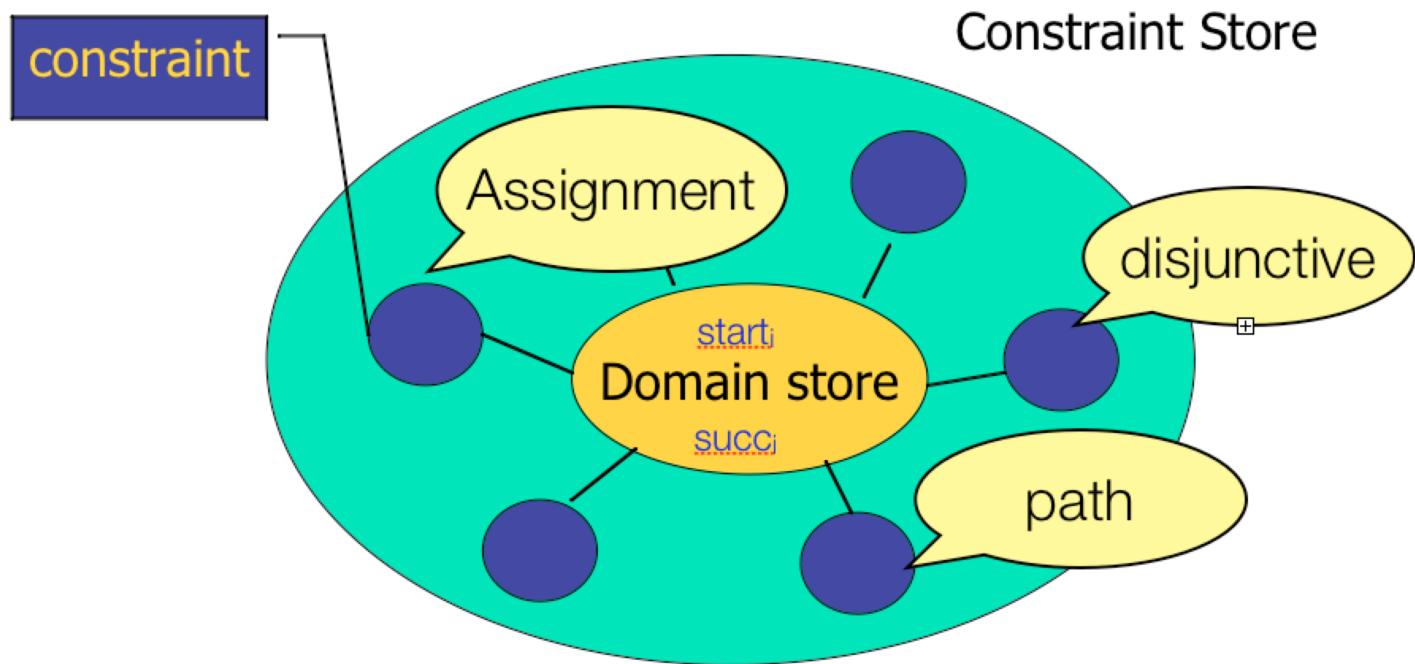
- Scheduling Model
  - reasons about the start dates, time windows
  - disjunctive constraint
- Routing Model
  - reasons about the successor/predecessor
  - Hamiltonian path constraints
  - assignment constraint for the transition times
- Communication constraints

# The Assignment Constraint

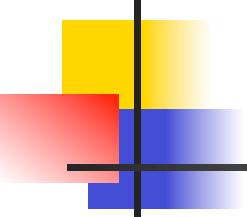




# Constraint Solving



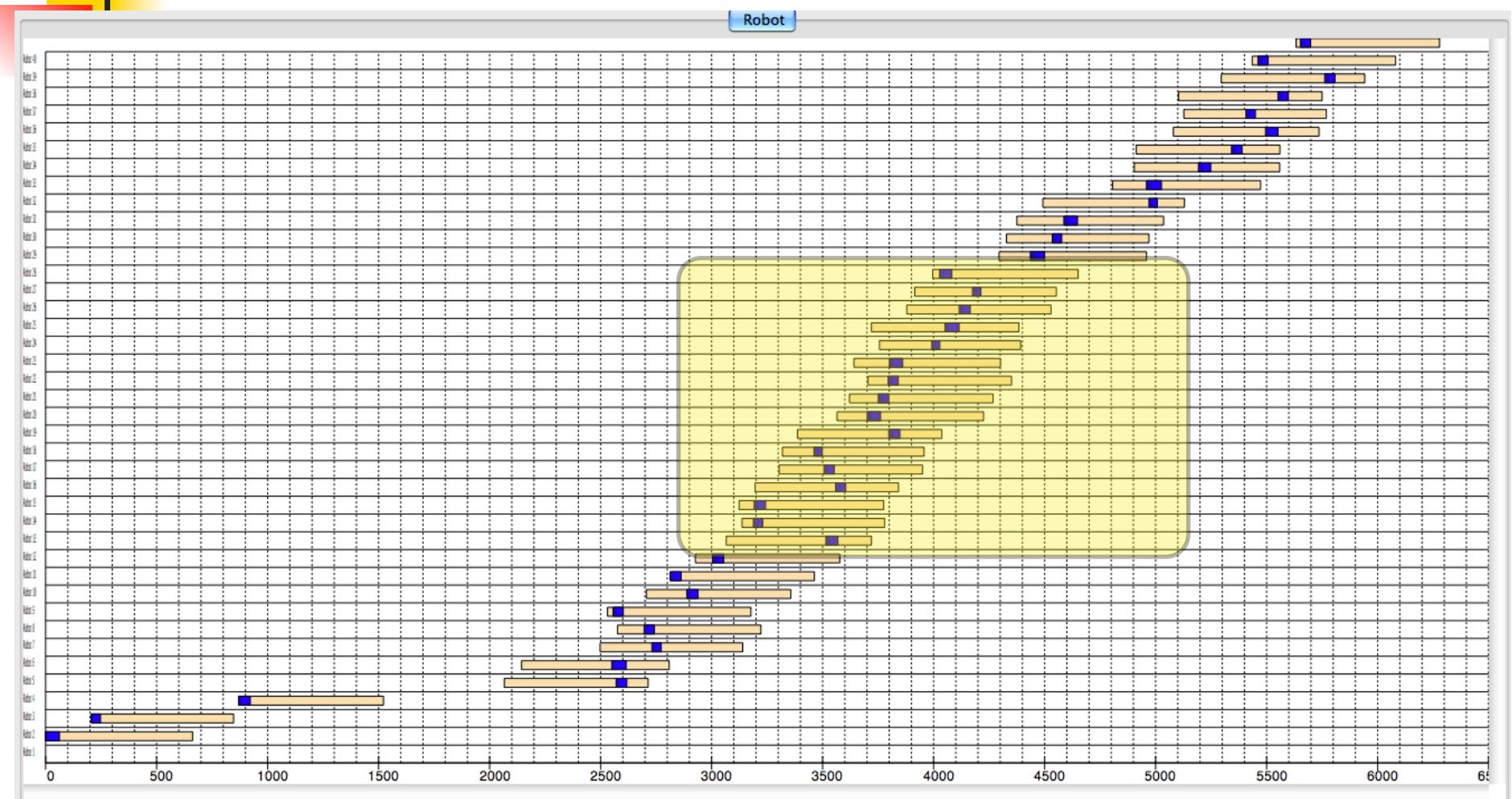
Pascal Van Hentenryck



# Large Neighborhood Search

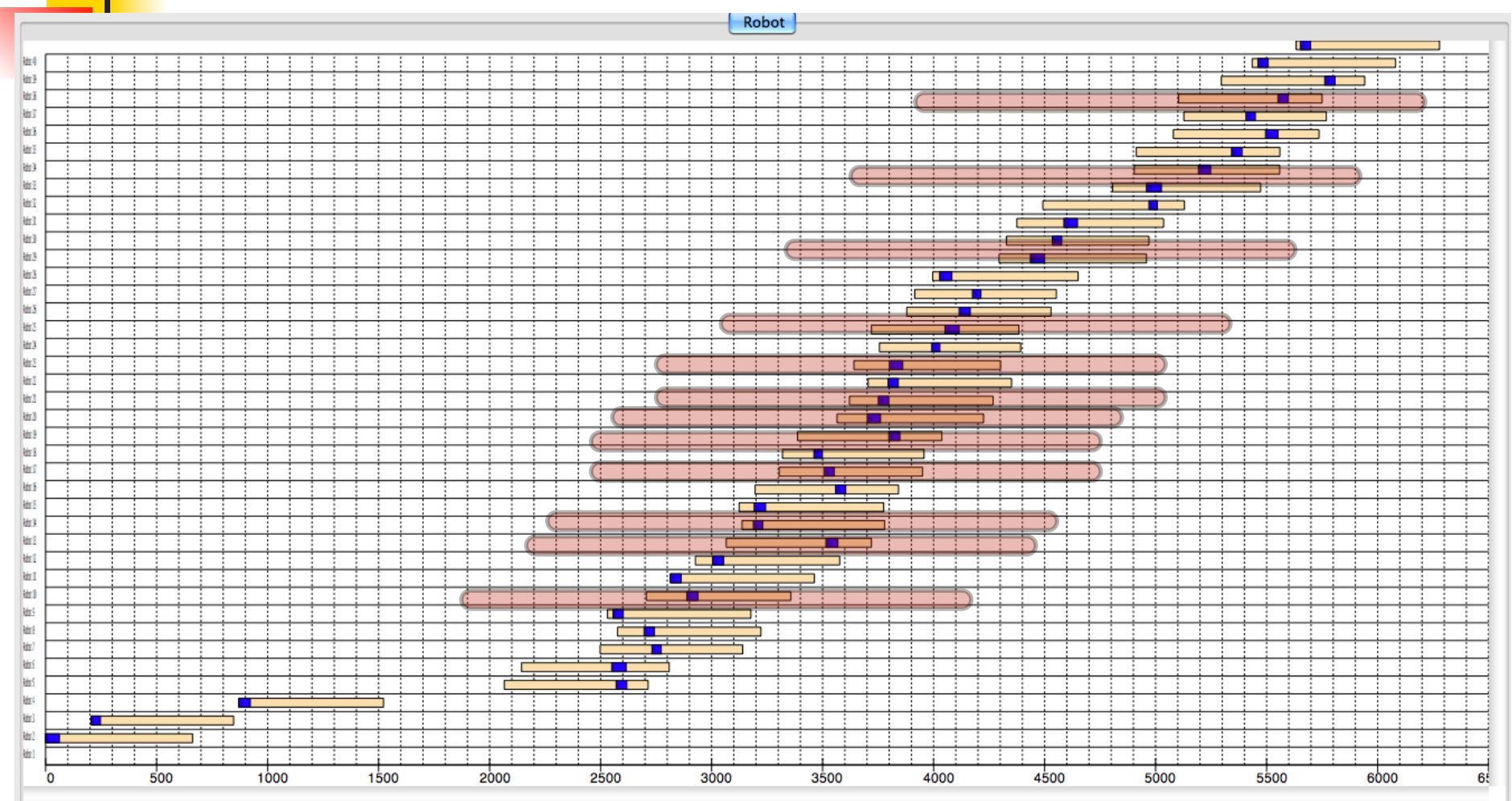
- Combination of local search and CP
  - start with a feasible solution (CP)
  - relax part of the best solution found so far
    - select a subpath in the solution
    - select a random set of variables
  - optimize the resulting problem using CP
    - it is a very constrained combinatorial space
  - iterate the last two steps

# Asymmetric TSP with Time Windows



Pascal Van Hentenryck

# Asymmetric TSP with Time Windows



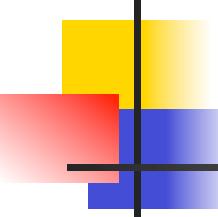
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# Experimental Results

	BK	300s	600s
40	386	386	
48	492	487	
49	488	484	
50	414	414	
67	1048	1048	
86	1052	1051	
92	1111	1093	
125	1410	1409	
132	1400	1382	
152	1792	1783	
172	1897	1870	1799
193	2452		2433
201	2296		2234
233	2786		2683

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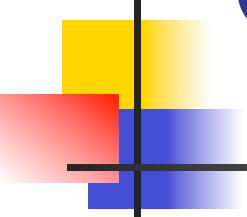
- ▶ Ascheuer, Fischetti, Grötschel, 2001
- ▶ industrial application in robotic
- ▶ 5 hours of CPU Time



# Cumulative Scheduling

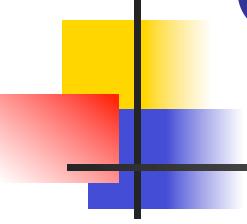
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- Problem formulation
  - a set of tasks is given, e.g., 1..100
  - each task  $t$  has a duration  $d(t)$
  - each task  $t$  has a machine  $m(t)$  to execute
  - a set of precedence constraints  $(b,a)$ 
    - $a$  can only start when  $b$  is completed
  - each machine has a capacity, i.e., a maximum number of activities that can be executed simultaneously
- Goal
  - minimize the project completion time



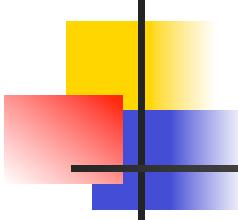
# Cumulative Scheduling

```
int capacity = 8; int nbTasks = 34;  
range Tasks = 1..nbTasks;  
int duration[Tasks] = ...  
int totalDuration = sum(t in Tasks) duration[t];  
int demand[Tasks] = ...  
tuple P { int before; int after; }  
set{P} setOfPrecedences = ...  
  
Scheduler<CP> cp(totalDuration);  
Activity<CP> a[t in Tasks](cp,duration[t]);  
DiscreteResource<CP> d(cp,capacity);  
Activity<CP> makespan(cp,0);
```



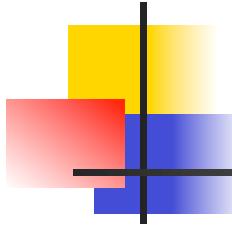
# Cumulative Scheduling

```
minimize<cp>
    makespan.end()
subject to {
    forall(t in Tasks)
        a[t].precedes(makespan);
    forall(p in setOfPrecedences)
        a[p.before].precedes(a[p.after]);
    forall(t in Tasks)
        a[t].requires(d,demand[t]);
} using {
    setTimes(a);
}
```



# Cumulative Scheduling Search

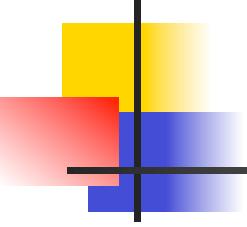
- Basic ideas
  - Not sufficient to order the tasks
  - Must choose starting times for the tasks
- Value/Variable Search
  - Choose the earliest time at which an activity can be scheduled
  - Nondeterministically choose an activity to start there
  - May use dominance rules to decide which activities to consider



# Large Neighborhood Search

---

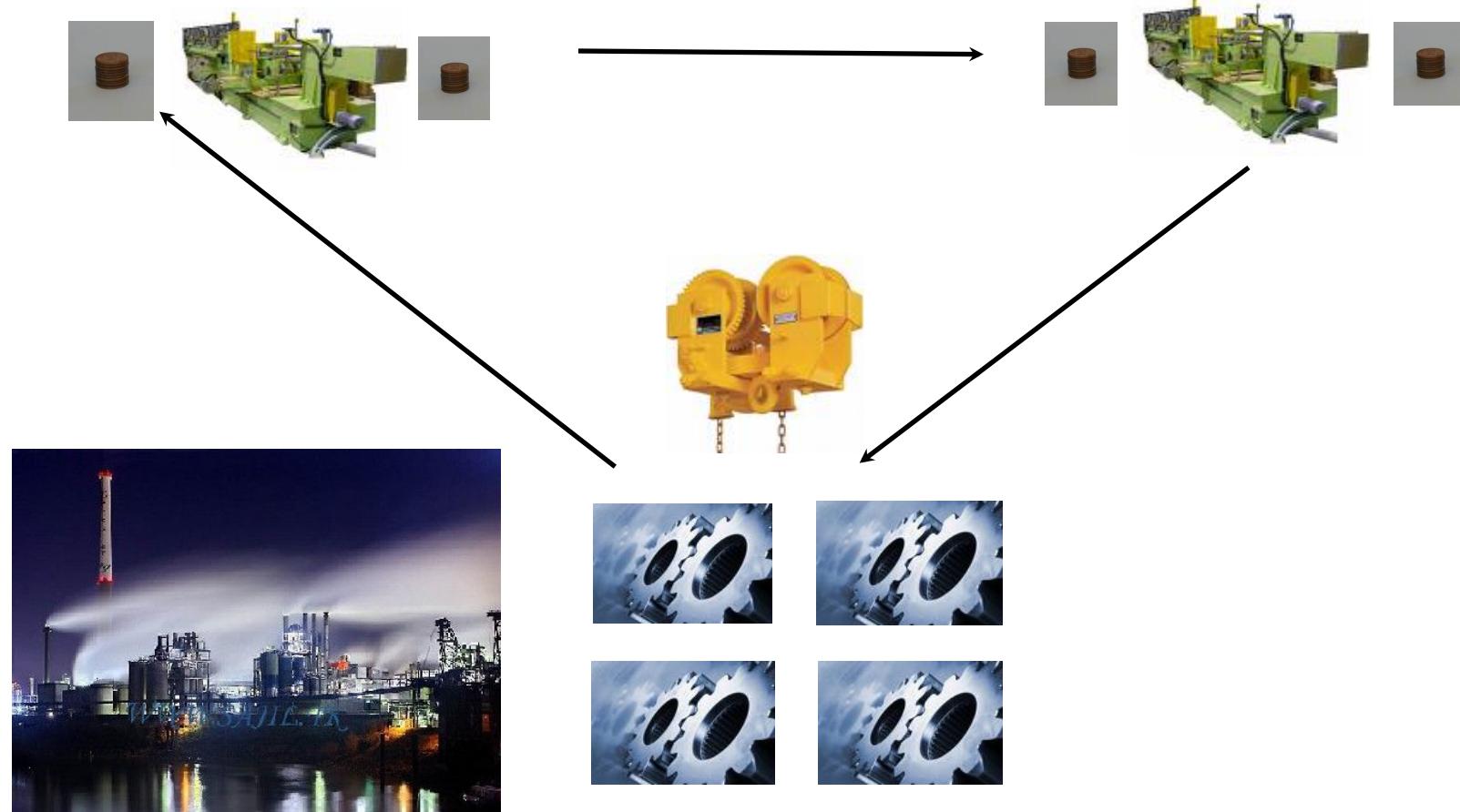
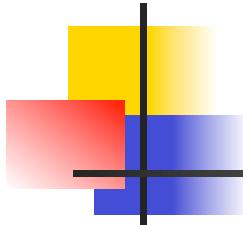
- Key idea: partial order schedule
- First step
  - relax a number of activities
  - remove them from the schedule
- Second step
  - use the resources to impose new precedence constraints
  - do not fix variables to their values



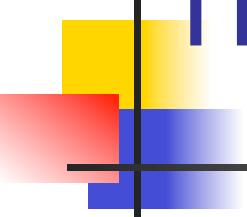
# Cumulative Scheduling

```
minimize<cp>
  makespan.end()
subject to { ...}
using setTimes(a);
onRestart {
  Solution s = cp.getSolution();
  if (s!=null) {
    set{Activity<CP>} R();
    forall(a in Activities)
      if (distr.get() <= Pr)
        R.insert(a);
    cp.relaxPOS(s,R);
  }
}
```

# The Trolley Problem



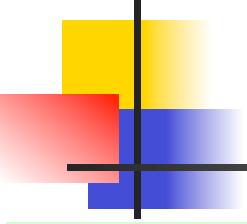
Pascal Van Hentenryck



# The Trolley Problem

- Model the trolley as a state resource
  - the state represents the location of the trolley
  - all activities use the trolley except the actual processing on the machine



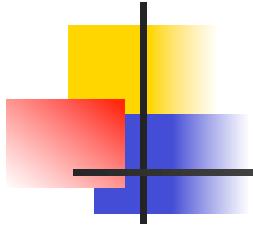


# The Trolley Problem (I)

```
enum Jobs = {j1,j2,j3,j4,j5,j6};  
enum Tasks=  
{loadA,unload1,process1,load1,unload2,process2,load2,unloadS};  
enum Locations = {m1,m2,m3,areaA,areaS};  
Locations location[Jobs,Tasks];  
int duration[Jobs,Tasks];  
  
Scheduler<CP> cp(horizon);  
StateResource<CP> trolley(cp,Locations);  
UnaryResource<CP> machine[Locations](cp);  
Activity<CP> act[j in Jobs,t in Tasks](cp,duration[j,t],location[j,t]);  
Activity<CP> makespan(cp,0);
```

# The Trolley Problem (I)

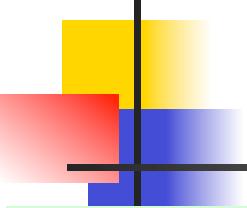
```
minimize<cp> makespan.end()
subject to {
    forall(j in Jobs, t1 in Tasks, t2 in Tasks: t1 < t2)
        act[j,t1].precedes(act[j,t2]);
    forall(j in Jobs) {
        act[j,process1].requires(machine[job[j].machine1]);
        act[j,process2].requires(machine[job[j].machine2]);
    }
    forall(j in Jobs, t in Tasks: t != process1 && t != process2)
        act[j,t].requires(trolley,location[j,t]);
    forall(j in Jobs)
        act[j,unloadS].precedes(makespan);
}
using {
    setTimes(all(j in Jobs, t in Tasks) act[j,t]);
    label(makespan.start());
}
```



# The Trolley Problem (II)

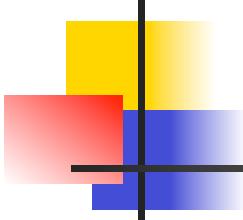
- Adding transition times between the machines

```
int tt[Locations,Locations] = [
    [ 0, 50, 60, 50, 90 ],
    [ 50, 0, 60, 90, 50 ],
    [ 60, 60, 0, 80, 80 ],
    [ 50, 90, 80, 0, 120 ],
    [ 90, 50, 80, 120, 0 ]
];
```



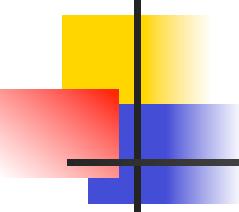
# The Trolley Problem (II)

```
enum Jobs = {j1,j2,j3,j4,j5,j6};  
enum Tasks=  
{loadA,unload1,process1,load1,unload2,process2,load2,unloadS};  
enum Locations = {m1,m2,m3,areaA,areaS};  
Locations location[Jobs,Tasks];  
int duration[Jobs,Tasks];  
  
Scheduler<CP> cp(horizon);  
StateResource<CP> trolley(cp,Locations,tt);  
UnaryResource<CP> machine[Locations](cp);  
Activity<CP> act[j in Jobs,t in Jobs](cp,duration[j,t],location[j,t]);  
Activity<CP> makespan(cp,0);
```



# The Trolley Problem (III)

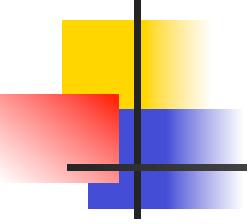
- Adding a capacity on the Trolley
  - Use activities to track when a job uses the trolley
  - Use a discrete resource
- The trolley is modeled by two resources
  - a state resource to denote its location
  - a discrete resource to denote its load
- Synchronization constraints



# The Trolley Problem (III)

## ■ Resources + Activities

```
enum TrolleyTasks = {onTrolleyA1,onTrolley12,onTrolley2S};  
Scheduler<CP> cp(horizon);  
UnaryResource<CP> machine[Locations](cp);  
StateResource<CP> trolley(cp,Locations);  
DiscreteResource<CP> trolleyCapacity(cp,3);  
Activity<CP> act[j in Jobs,t in Jobs]  
    (cp,duration[j,t],location[j,t]);  
Activity<CP> tact[j in Jobs,t in TrolleyTasks]  
    (cp,2*loadDuration..horizon);  
Activity<CP> makespan(cp,0);
```



# The Trolley Problem (III)

## ■ Specifying the trolley activities

```
forall(j in Jobs) {  
    cp.post(tact[j, onTrolleyA1].start() == act[j, loadA].start());  
    cp.post(tact[j, onTrolleyA1].end() == act[j, unload1].end());  
    cp.post(tact[j, onTrolley12].start() == act[j, load1].start());  
    cp.post(tact[j, onTrolley12].end() == act[j, unload2].end());  
    cp.post(tact[j, onTrolley2S].start() == act[j, load2].start());  
    cp.post(tact[j, onTrolley2S].end() == act[j, unloadS].end());  
}  
forall(j in Jobs, t in TrolleyTasks)  
    tact[j, t].requires(trolleyCapacity, 1);
```