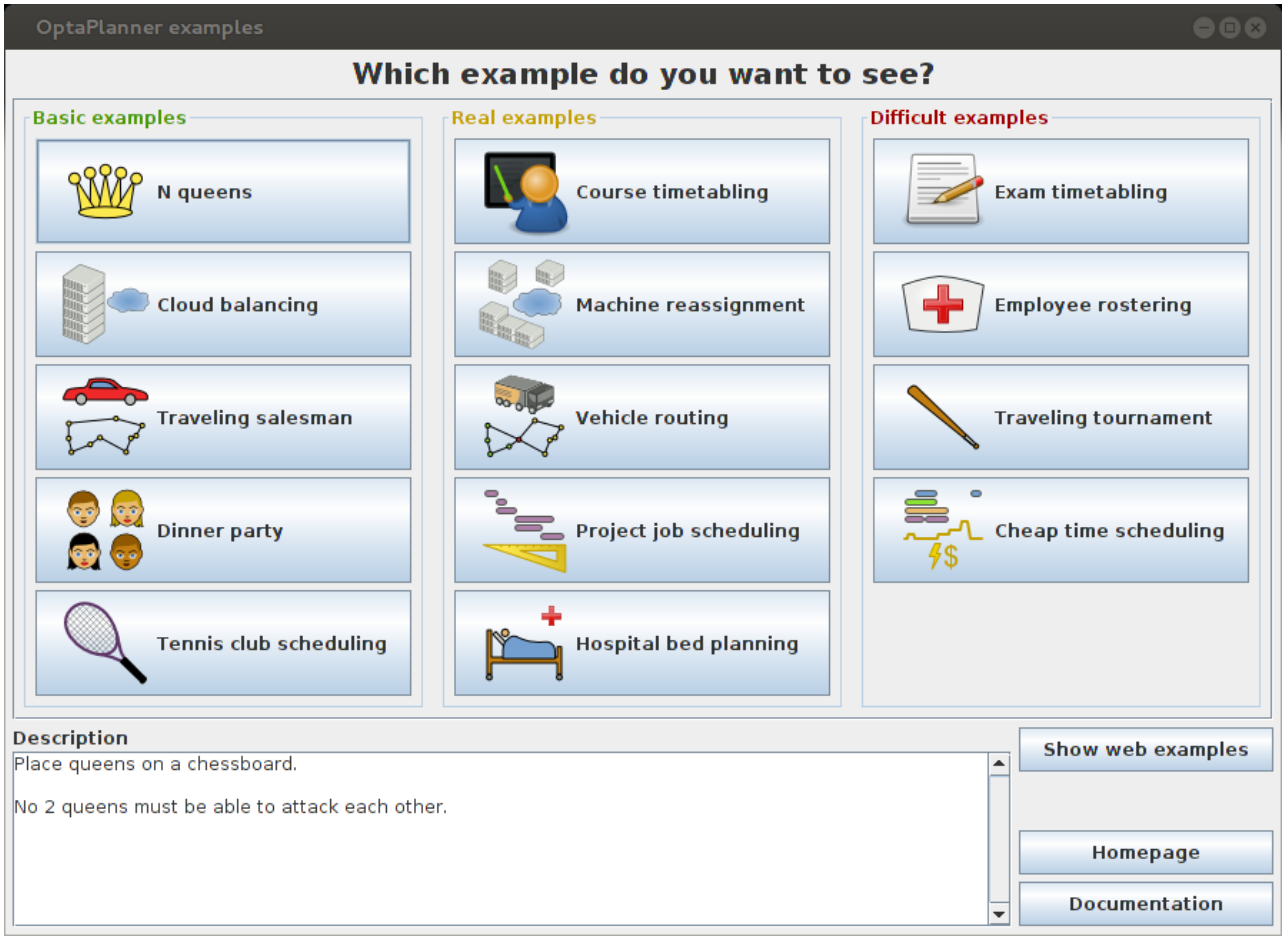
Do more business with less resources

by Geoffrey De Smet

OptaPlanner lead

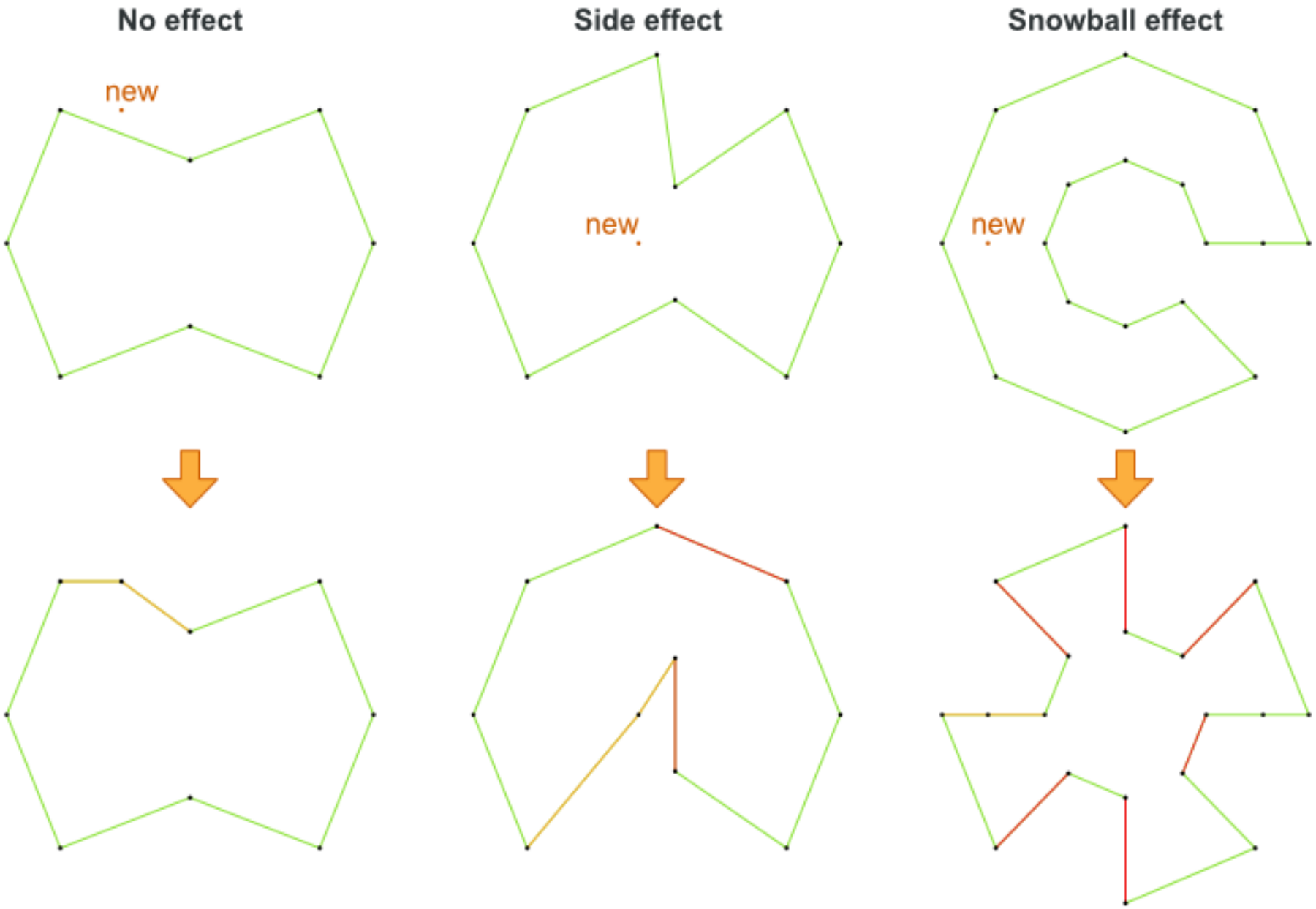
What is business resource optimization?



TSP demo

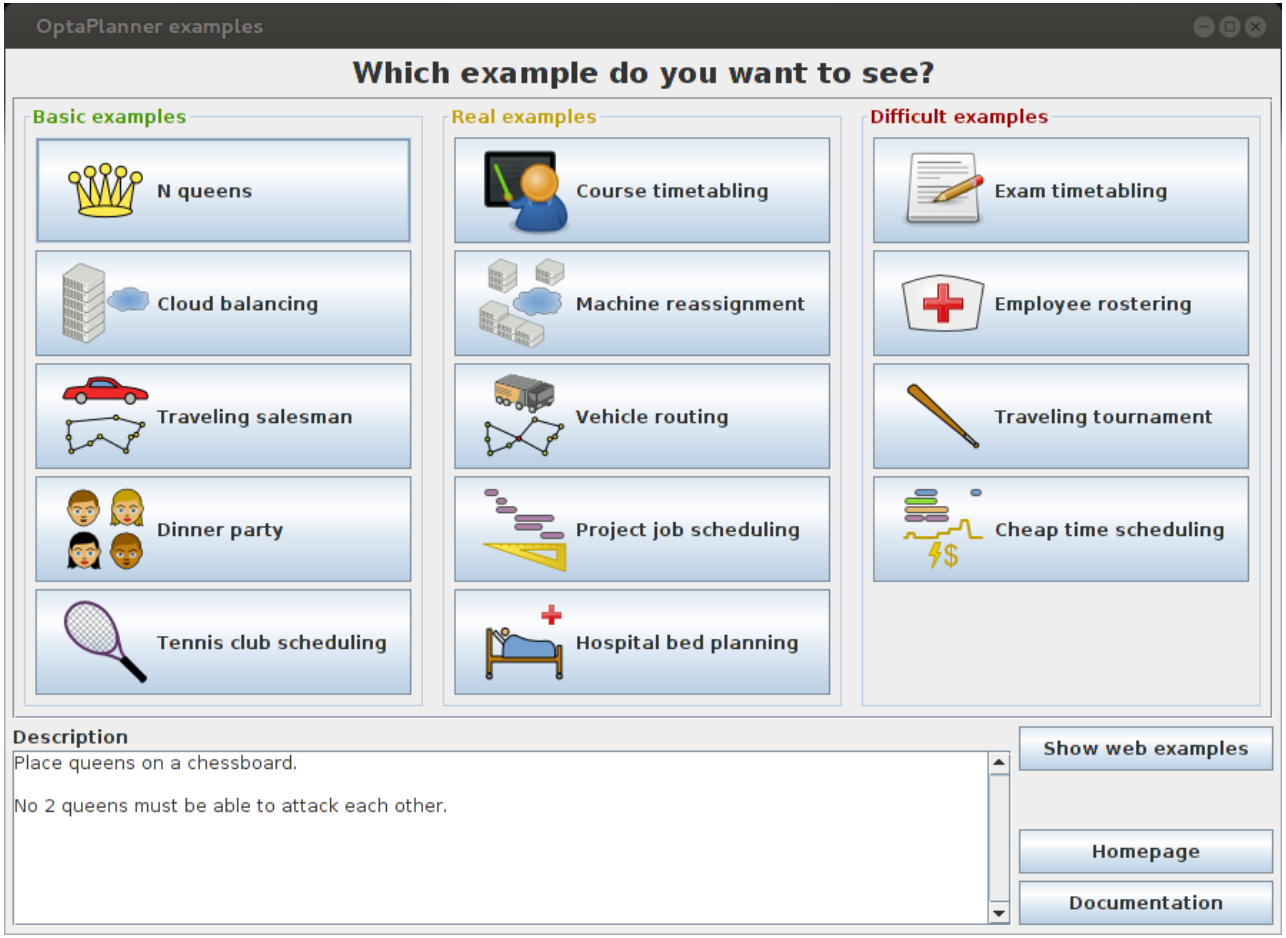
TSP optimal solution volatility

How much does the optimal solution change if we add 1 new location?



TSP
is an academic problem

What is realistic business resource optimization?



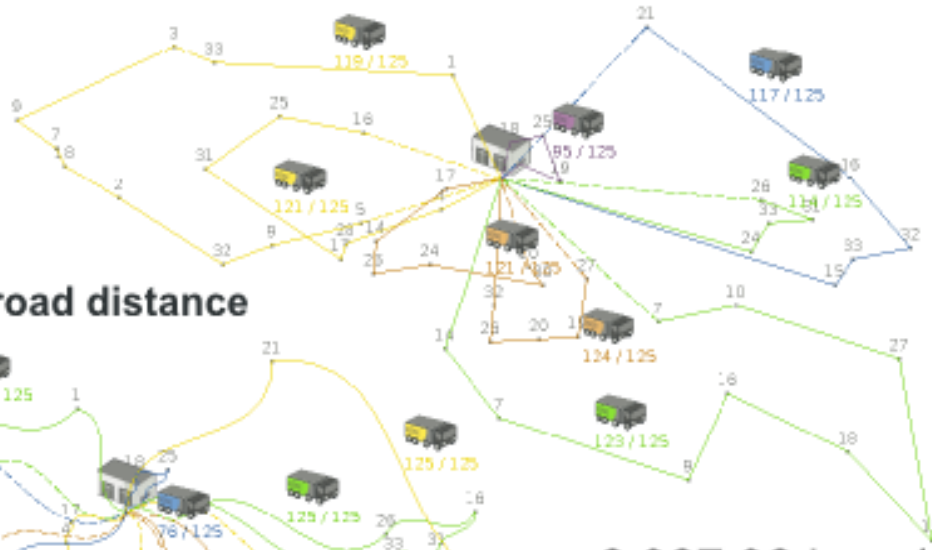
VRP demo

Vehicle routing distance type

Can we optimize for air distances, when we need road distances or driving times?

Optimized for ...

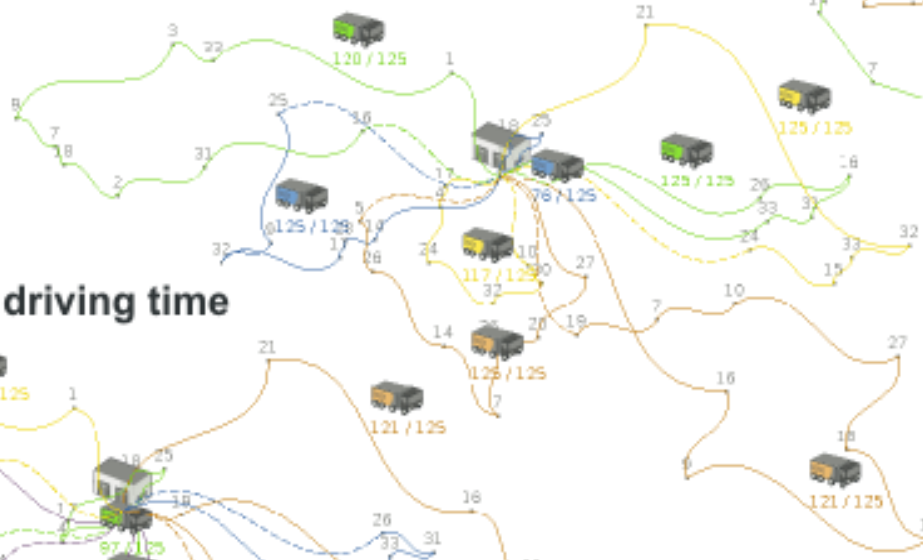
... air distance



2 327.32 km 118 632 sec

3.8% worse 4.0% worse

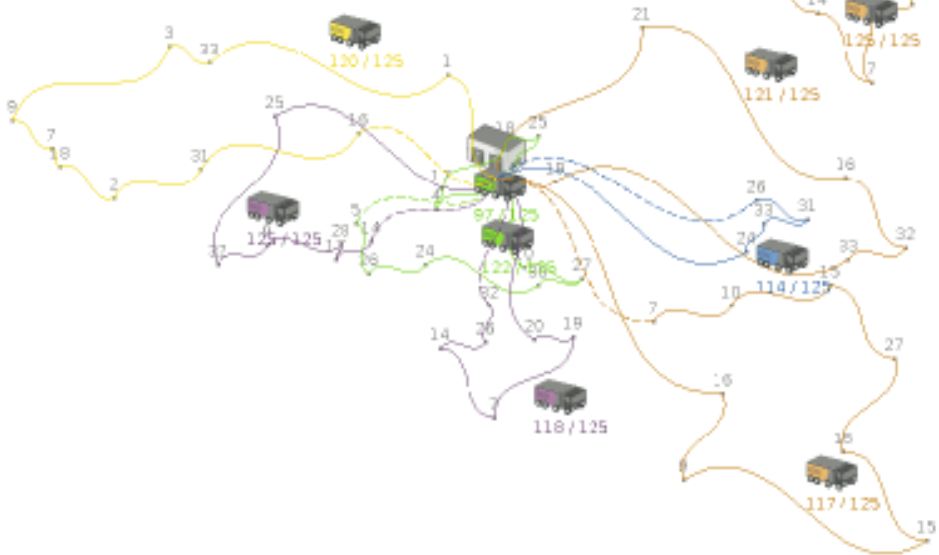
... road distance



2 243.15 km 115 516 sec

best 1.2% worse

... driving time



2 300.32 km 114 105 sec

2.5% worse best

Integration with real maps

Google Maps or GraphHopper (OpenStreetMap) calculate distances, OptaPlanner optimizes the trips.

Locations
with latitude and longitude

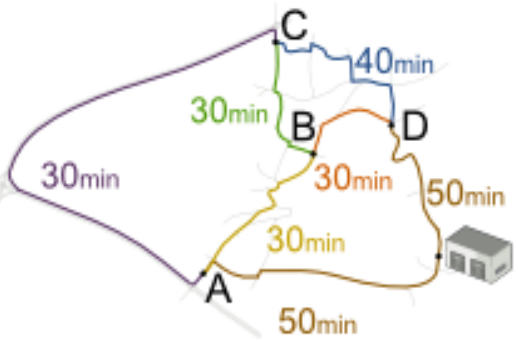
Google Maps
REST Client

or

GraphHopper
REST *or* local

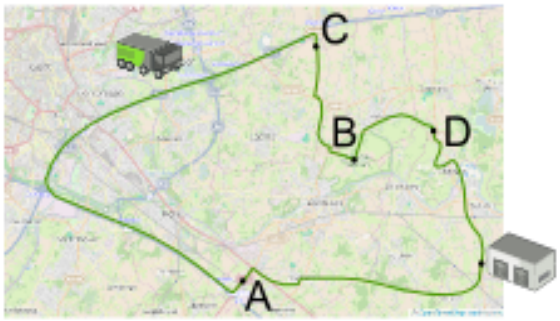
Fetch distance matrix
for every pair of locations

from \ to		A	B	C	D
	0	50	80	90	50
A	50	0	30	30	60
B	80	30	0	30	30
C	90	32	30	0	40
D	50	60	30	40	0



OptaPlanner

Render in browser



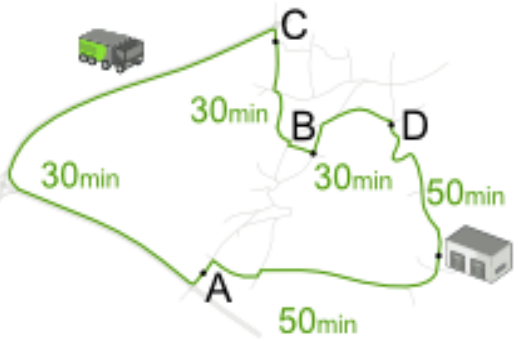
Google Maps
JavaScript

or

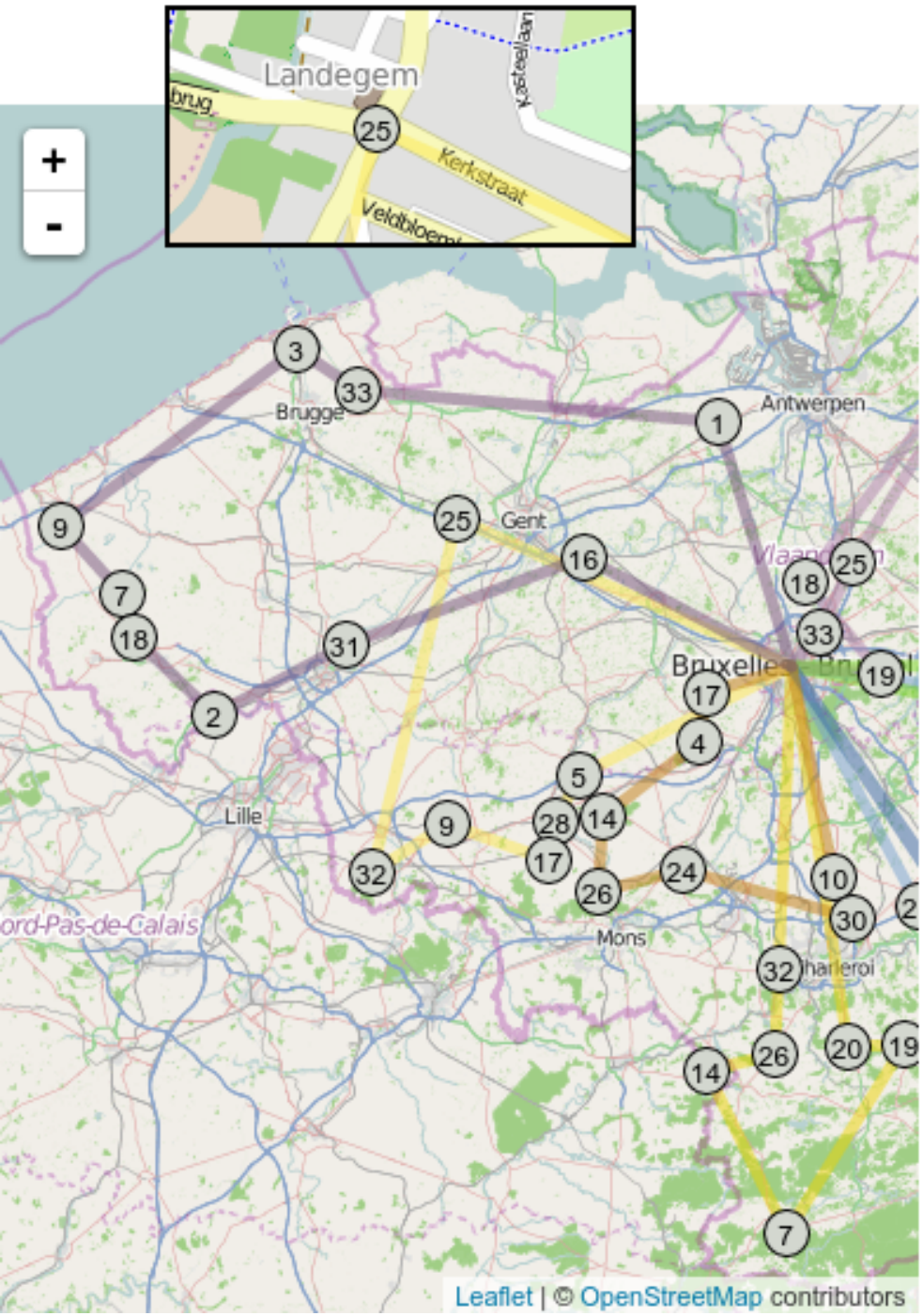
Leaflet.js
JavaScript

Optimize trips
under hard and soft constraints

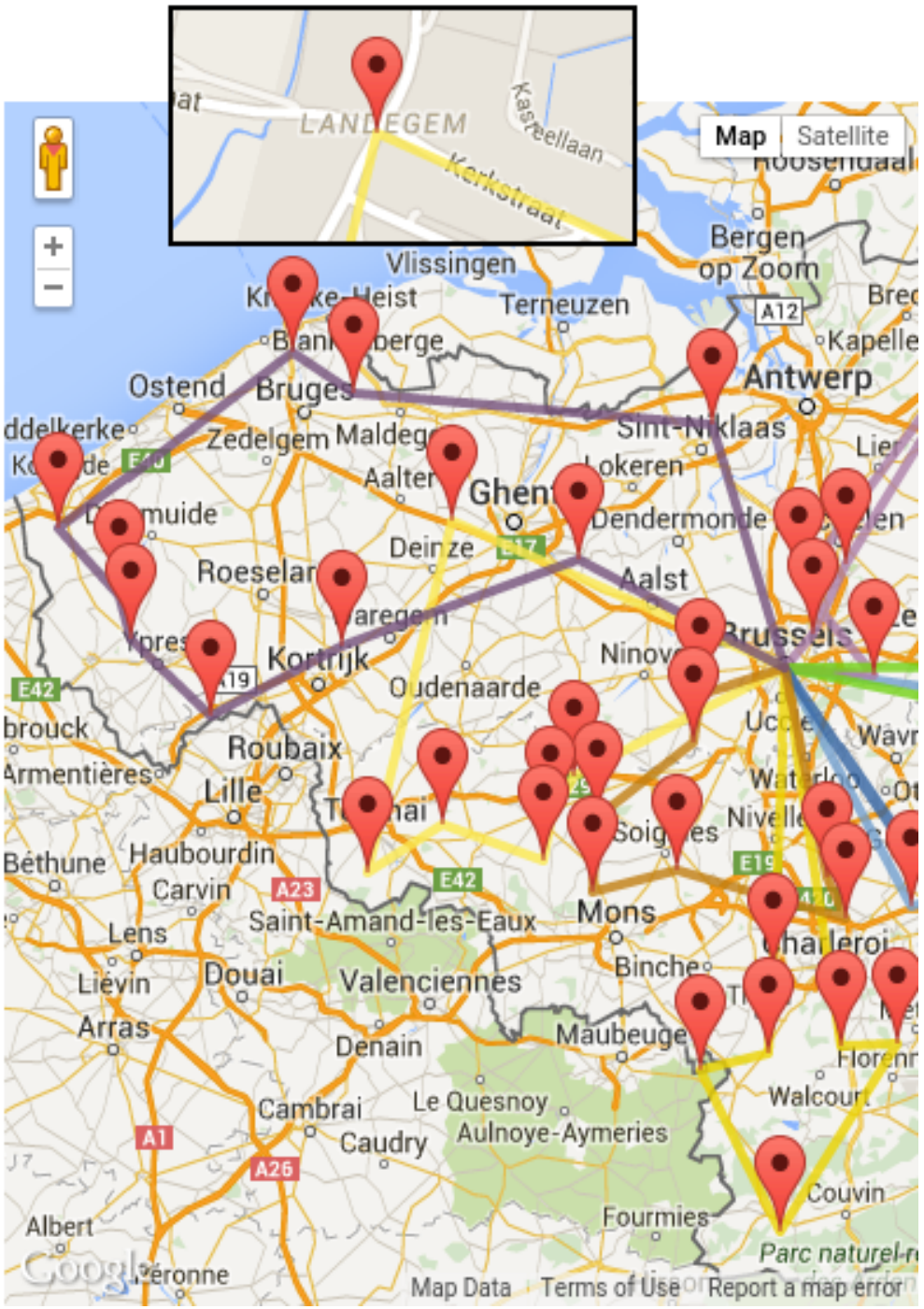
from \ to		A	B	C	D
	0	50	80	90	50
A	50	0	30	30	60
B	80	30	0	30	30
C	90	32	30	0	40
D	50	60	30	40	0



Leaflet.js



Google Maps




Map
Satellite
Middelburg
Vlissingen
Terneuzen
Bergen op Zoom
Eindhoven
Deurne
Venlo
Valkenswaard
Turnhout
Antwerp
Kapellen
Lommel
Weert
Roermond
Ostend
Bruges
Middelkerke
Zedelgem
Maldeg
Sint-Niklaas
Lokeren
Lier
Geel
Mol
Dunkirk
Aalter
Ghent
Dendermonde
Beringen
Sittard
Erkelenz
Deinze
Aarschot
Roeselare
Aalst
Hasselt
Maastricht
Heerlen
Aachen
Oudenaarde
Leuven
Sint-Truiden
Hazebrouck
Armentières
Roubaix
Lille
Waterloo
Wavre
Verviers
Simmerath
Béthune
Haubourdin
Carvin
Saint-Amand-les-Eaux
Mons
Namur
Spa
Schleiden
Lens
Douai
Valenciennes
Binche
Sprimont
Malmedy
Liévin
Arras
Denain
Maubeuge
Dinant
Marche-en-Famenne
Cambrai
Le Quesnoy
Aulnoye-Aymeries
Caudry
Givet
Albert
Fourmies
Parc naturel régional des Ardennes
Hirson
Amiens
Péronne
Corbie
Saint-Quentin
Charleville-Mézières
Sedan
Tergnier
Noyon
Chauny
Laon
Rethel
Virton
Longwy
Luxembourg City
Saint-Just-en-Chaussée
Compiègne
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Terms of Use
Report a map error

What is a planning problem?

Optimize goals with limited resources under constraints

Optimize goals

- Maximize profit
- Minimize ecological footprint
- Maximize happiness of employees / customers
- ...

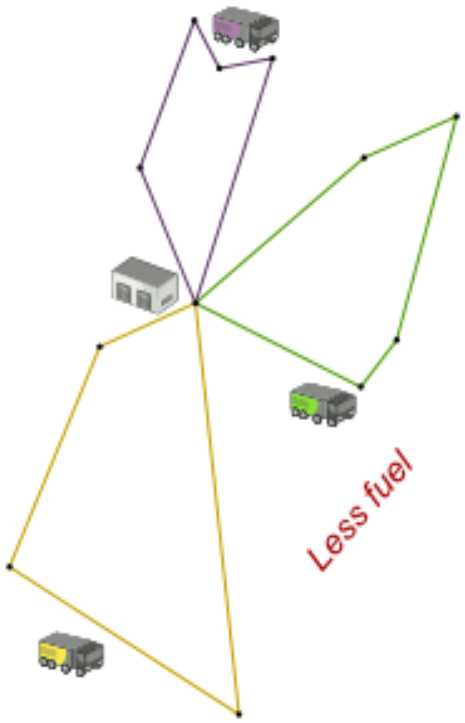
With limited resources

- Employees
- Assets (machines, buildings, vehicles, ...)
- Time
- Budget

Under constraints

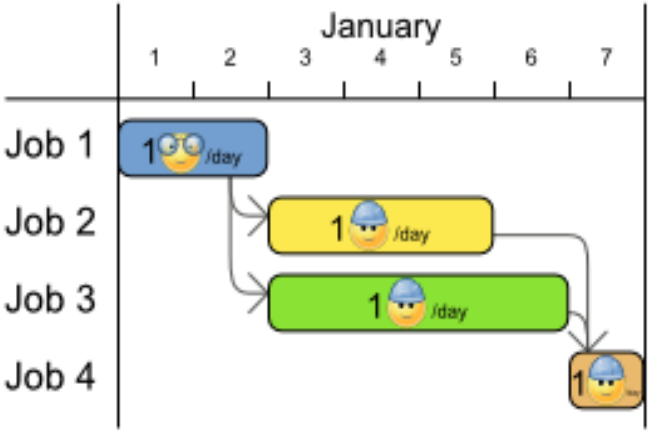
- vs Working hours
- vs Skills / affinity
- vs Logistic conflicts
- ...

Vehicle routing



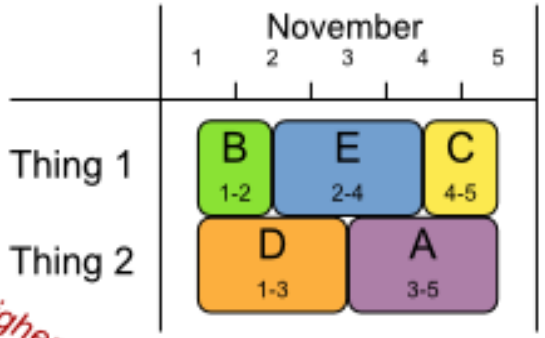
Less fuel

Job shop scheduling



Less makespan

Equipment scheduling



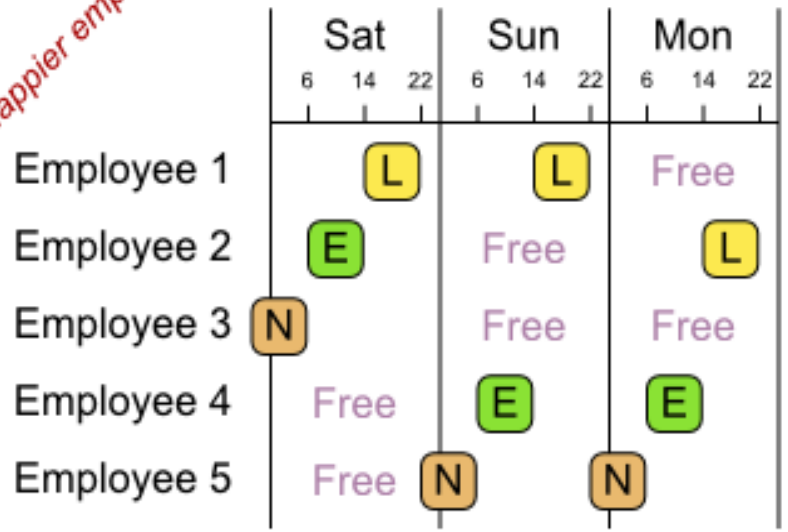
Higher utilization

OptaPlanner

Do more business with less resources

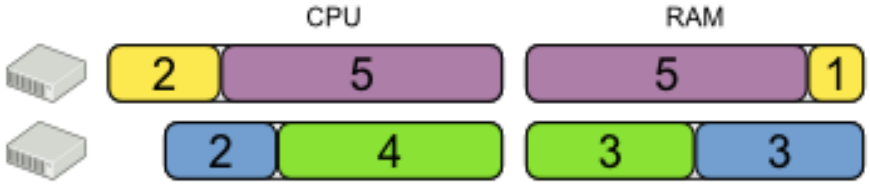
Happier employees

Employee rostering



Better allocations

Bin packing



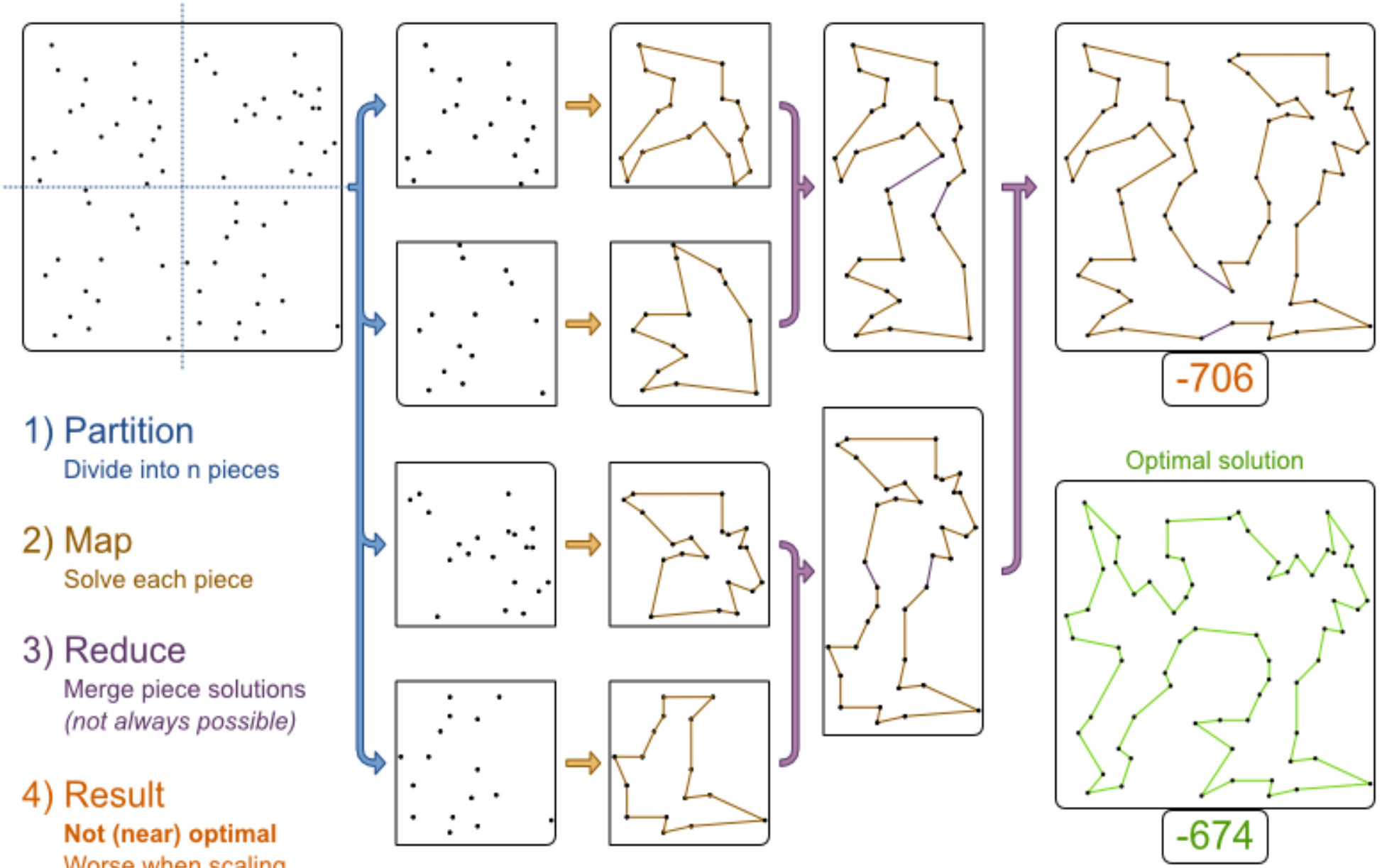
Planning problem use cases

- **Agenda scheduling**: doctor appointments, court hearings, maintenance jobs, TV advertisements, ...
- **Educational timetabling**: lectures, exams, conference presentations, ...
- **Task assignment**: affinity/skill matchmaking for tax audits, wage calc, ...
- **Employee shift rostering**: nurses, repairmen, help desk, firemen, ...
- **Vehicle routing**: route trucks, buses, trains, boats, airplanes, ...
- **Bin packing**: fill containers, trucks, ships, storage warehouses, cloud computers nodes, prisons, hospitals, ...
- **Job shop scheduling**: assembly lines for cars, furniture, books, ...
- **Cutting stock**: minimize waste while cutting paper, steel, carpet, ...
- **Sport scheduling**: football/baseball league, tennis court utilization, ...
- **Financial optimization**: investment portfolio balance, risk spreading, ...

Are planning problems difficult to solve?

MapReduce is terrible for TSP

Why do MapReduce, Divide&Conquer and partitioning perform badly on NP-hard problems?



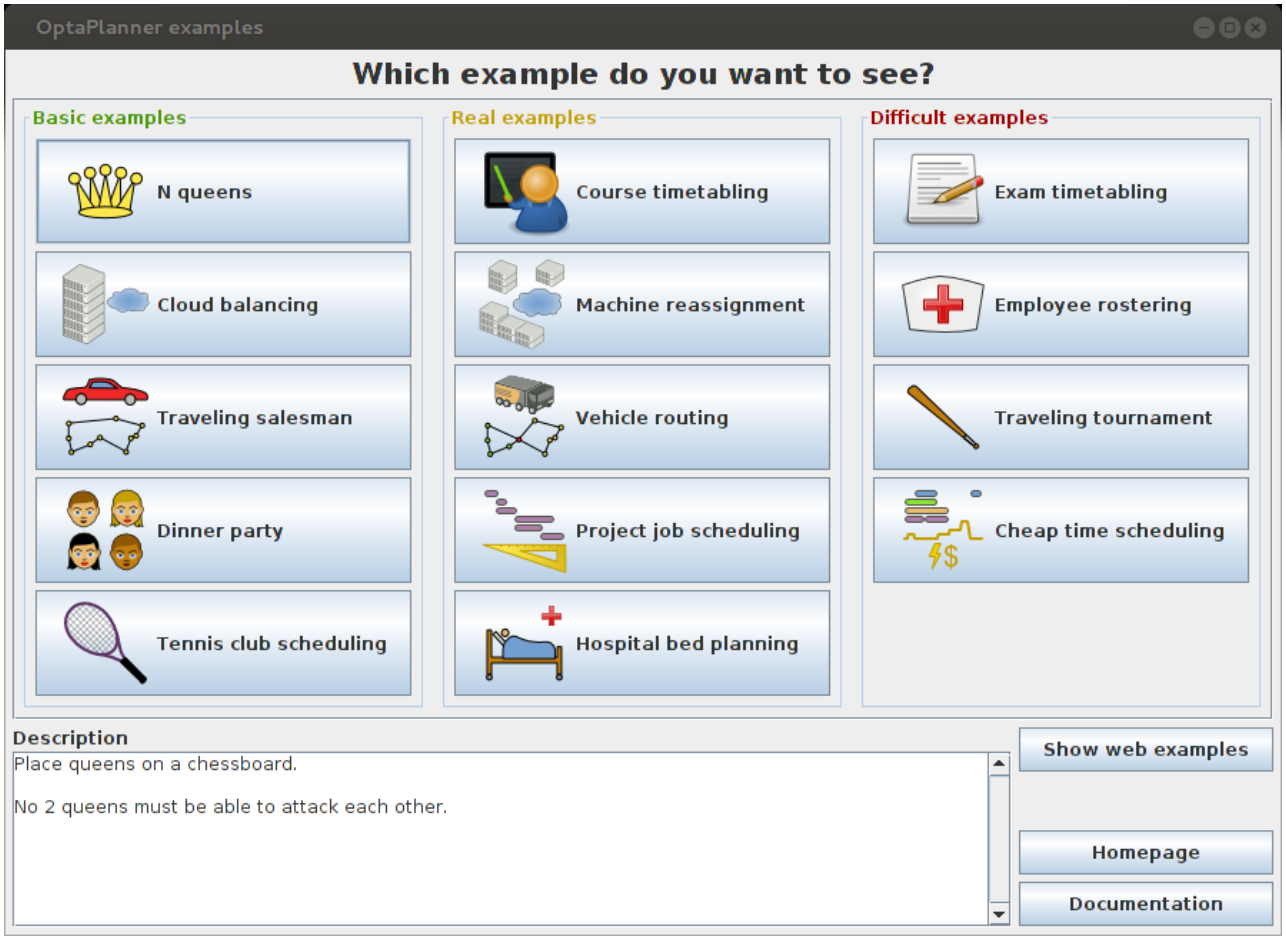
1) Partition
Divide into n pieces

2) Map
Solve each piece

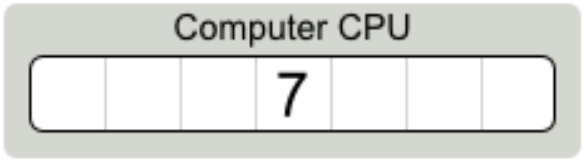
3) Reduce
Merge piece solutions
(not always possible)

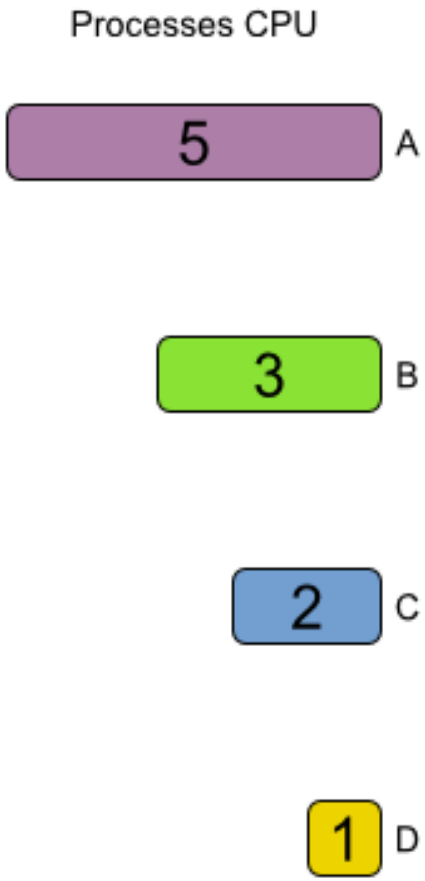
4) Result
Not (near) optimal
Worse when scaling

What is business resource optimization?

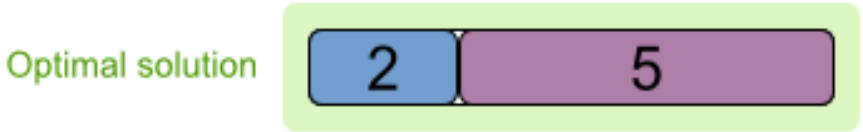


Cloud Balancing demo



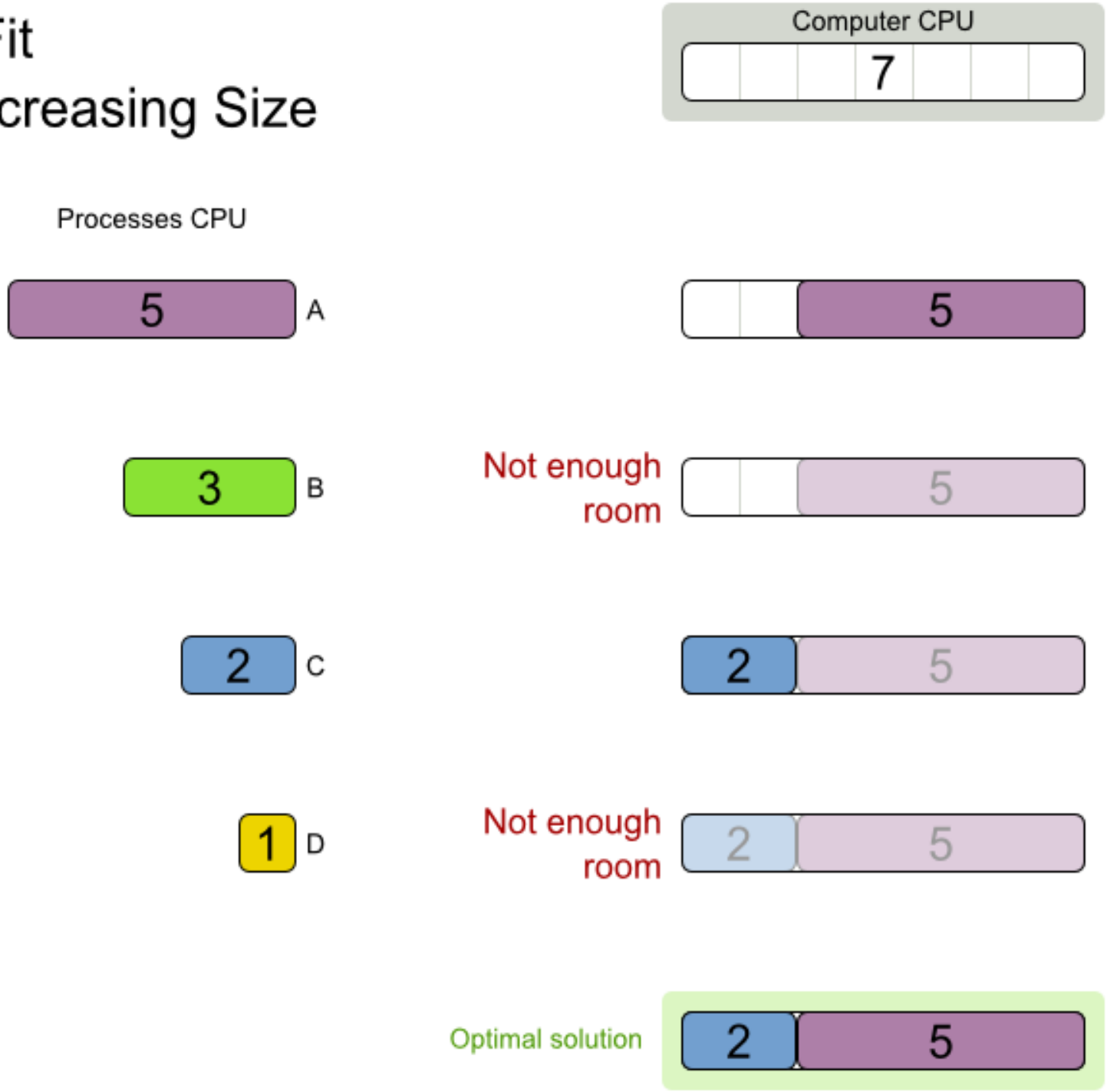


Which processes fill up this computer as much as possible?

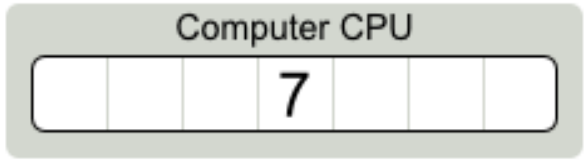


How did we find this solution?

First Fit
by Decreasing Size



First Fit Decreasing again...



Processes CPU

Not enough room

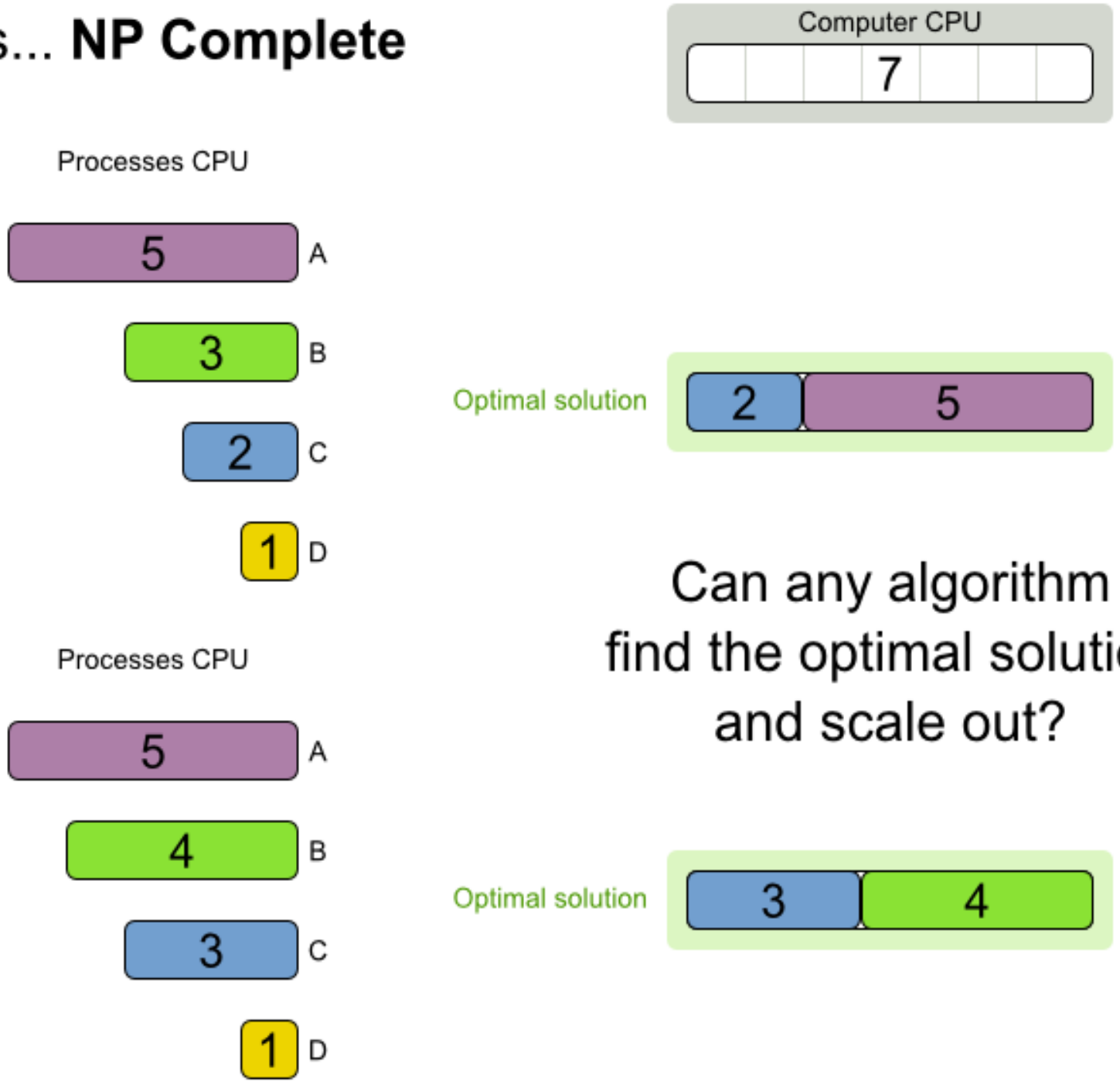
Not enough room

Not optimal!

FAIL

Optimal solution

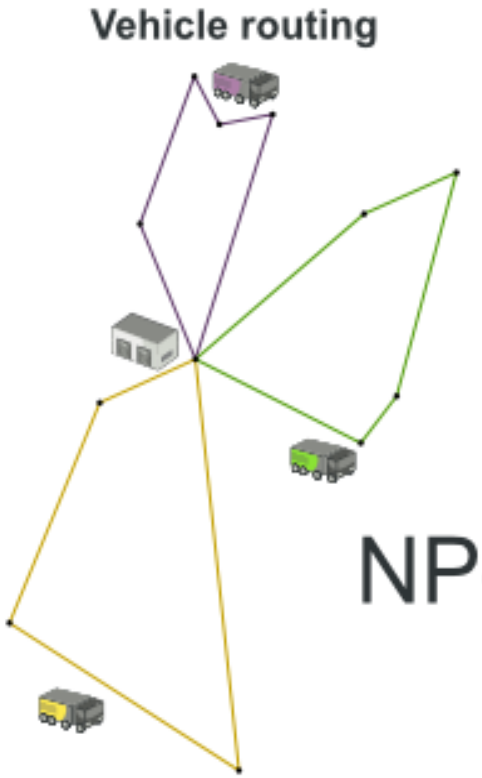
This is... **NP Complete**

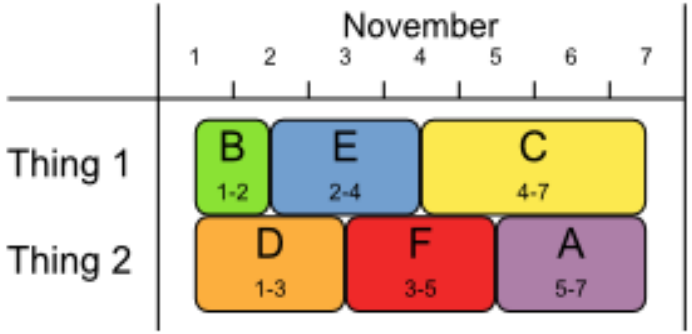


Find optimal solution and scale out for an NP-complete problem?

⇔ Is P = NP?

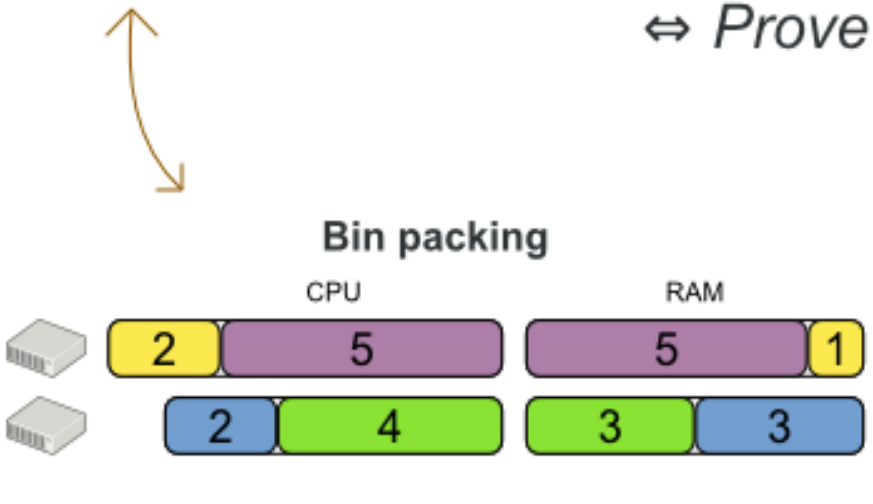
- Unresolved since 1971
- 1 000 000 $ reward since 2000
  - One of the 7 Millennium Problems (http://www.claymath.org/millennium-problems)
- Most believe P ≠ NP
  - ⇔ **Impossible to find optimal solution and scale out**
- 3000+ known NP-complete problems (wikipedia (http://en.wikipedia.org/wiki/List_of_NP-complete_problems))

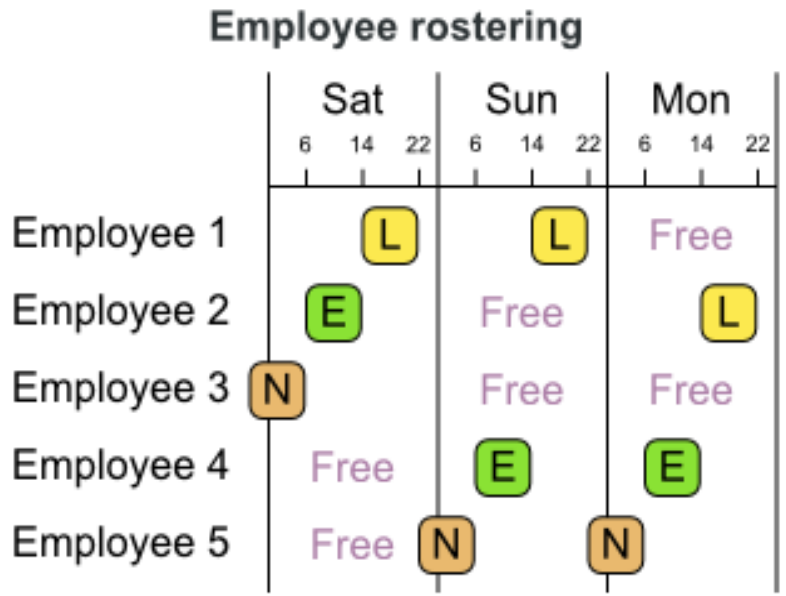




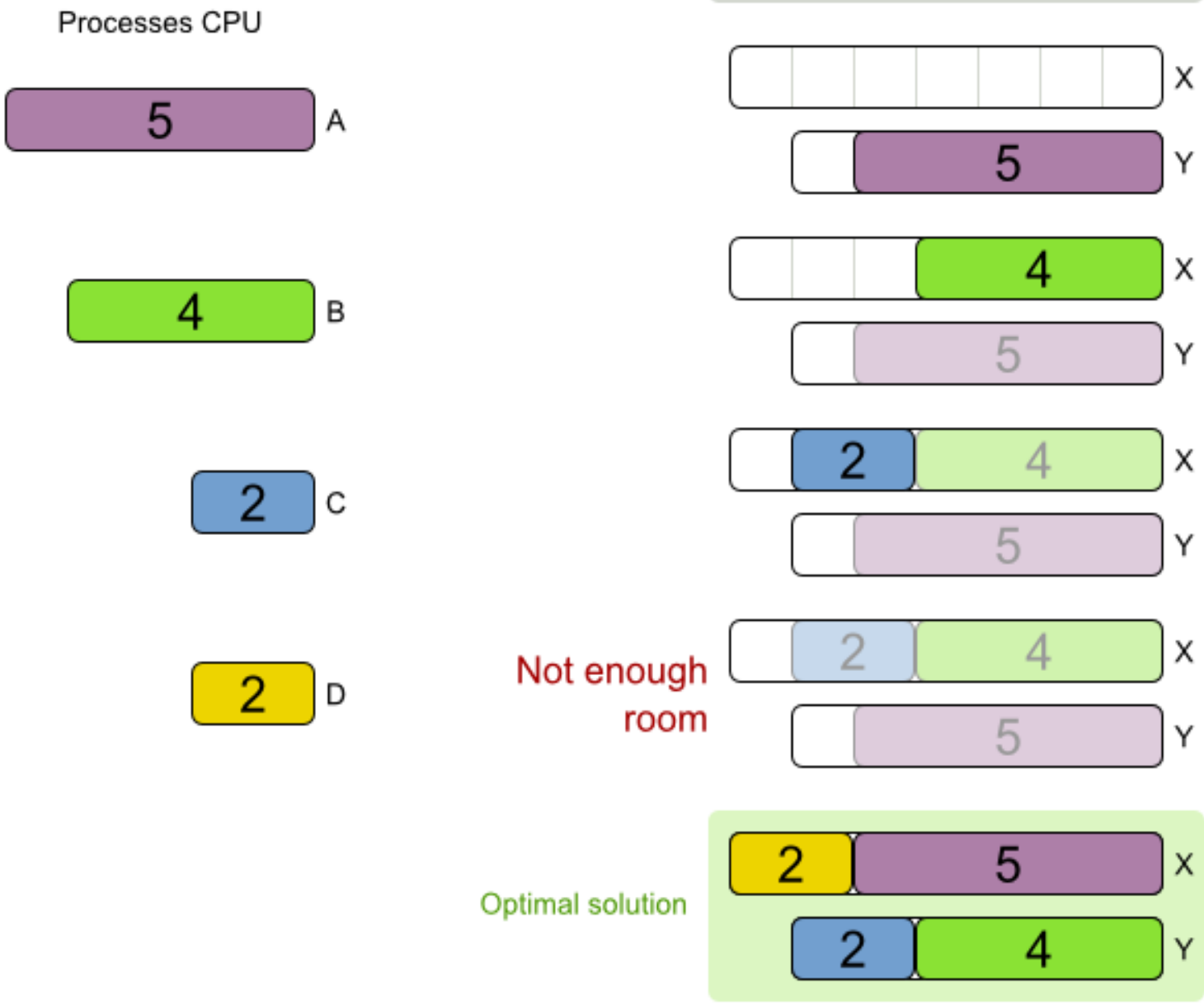
NP-complete interconnection

*Solve **one** use case*
*⇔ Solve **all** use cases*
⇔ Prove P = NP

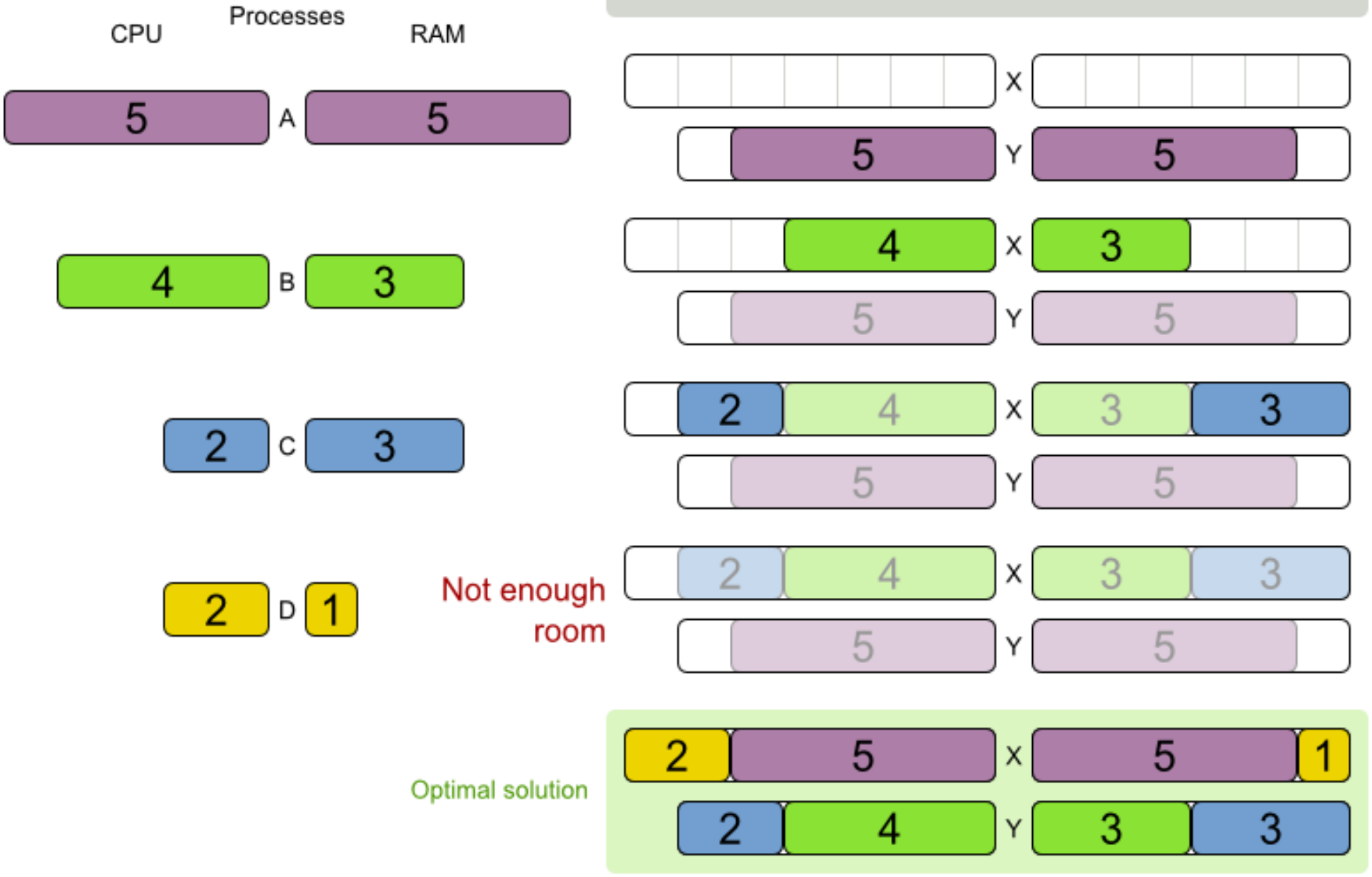




Multiple computers...
⇒ harder to solve

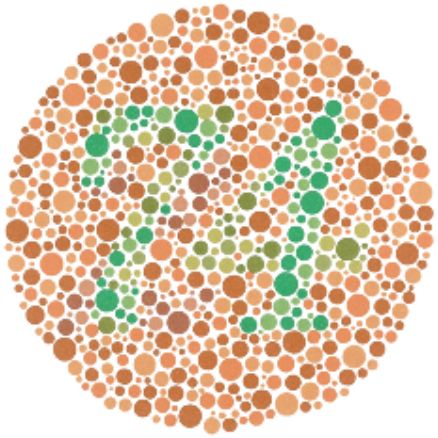


More constraints...
⇒ harder to solve



Planning problems are difficult to solve!

And human aren't good at it



But they don't realize it
(nor does their manager)

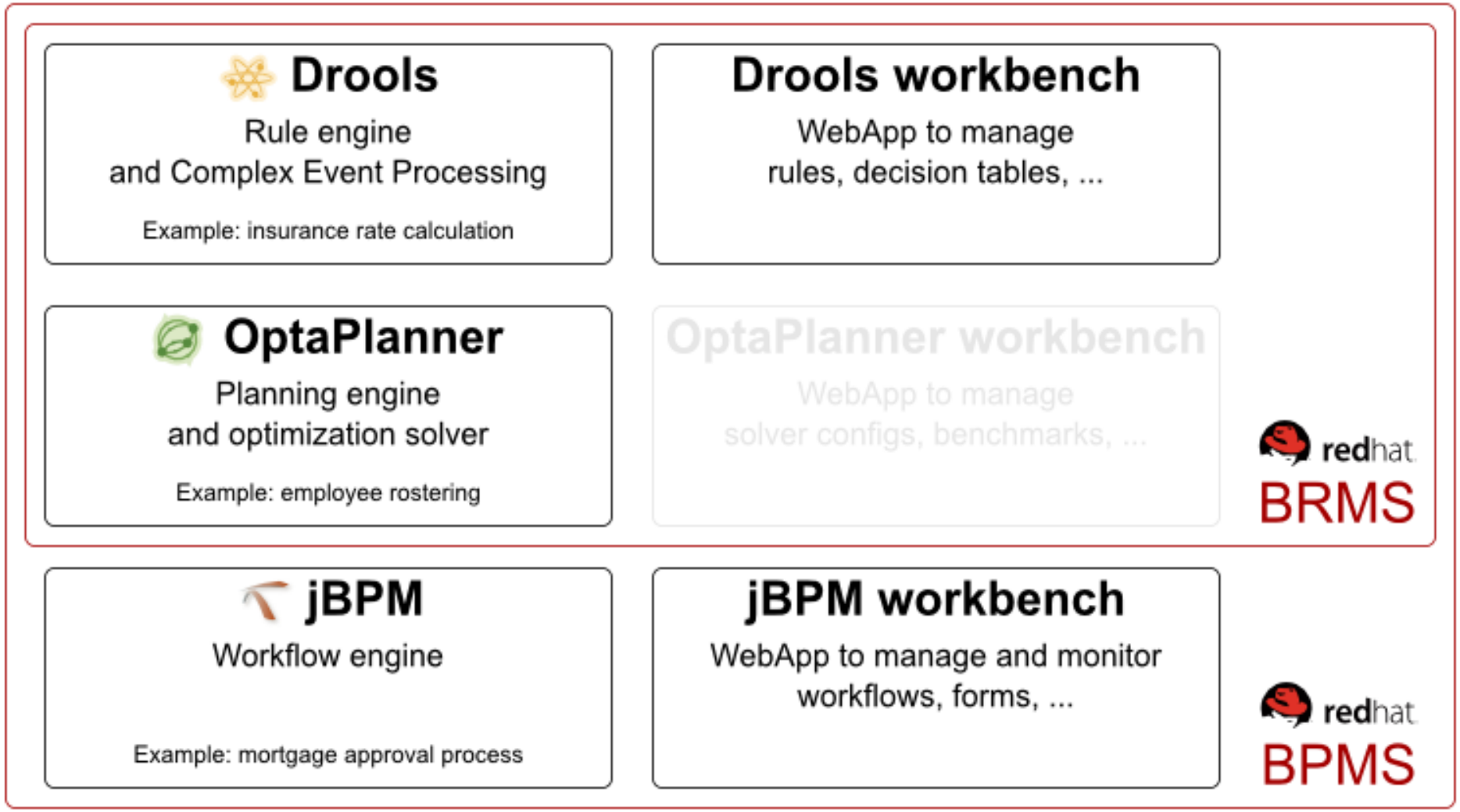
Reuse optimization algorithms

Find better solutions in time and scale out

- **Open source**
  Apache License
- **Regular releases**
  Download the zip or from Maven Central
- **Documented**
  Reference manual, examples, ...
- **Quality coverage**
  Unit, integration and stress tests

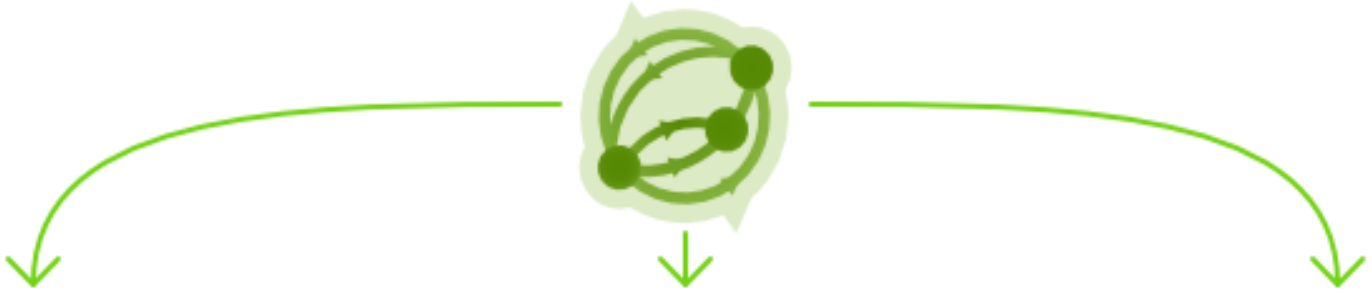
KIE functionality overview

What are the KIE projects?



Compatibility

OptaPlanner works on any Java Virtual Machine



Standard Java

Linux

Mac

Windows

...

Enterprise Java

OPENSHIFT

...

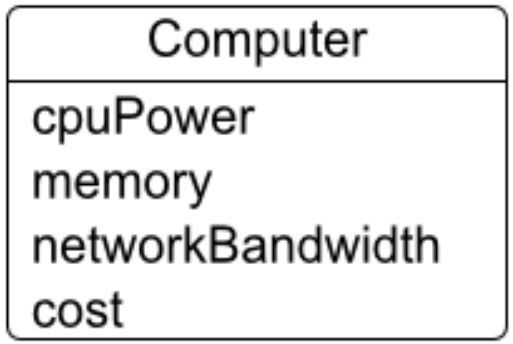
JVM languages

...

Cloud Balancing example

Domain model

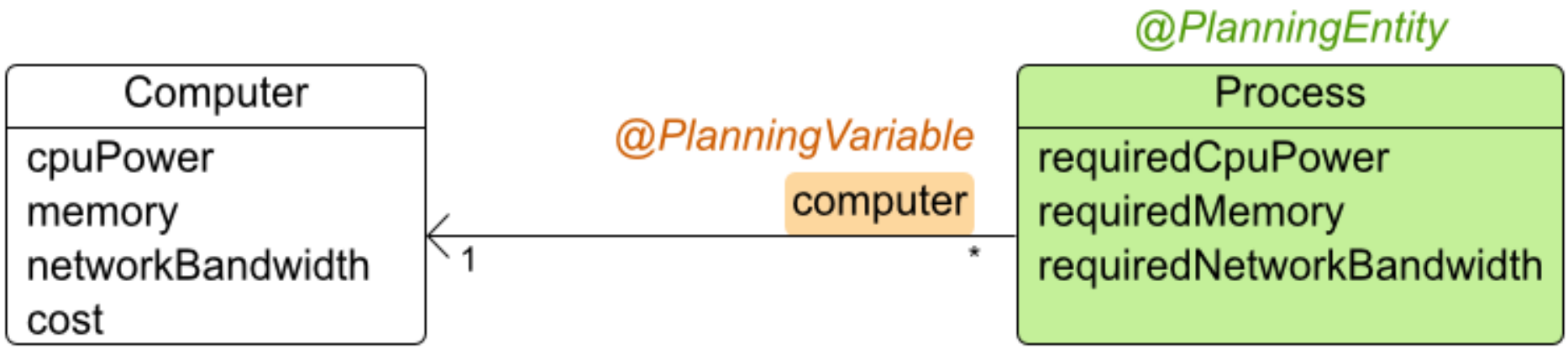
Cloud balance class diagram



Computer

```
public class Computer {

  private int cpuPower;
  private int memory;
  private int networkBandwidth;

  private int cost;

  // getters
}
```

Cloud balance class diagram



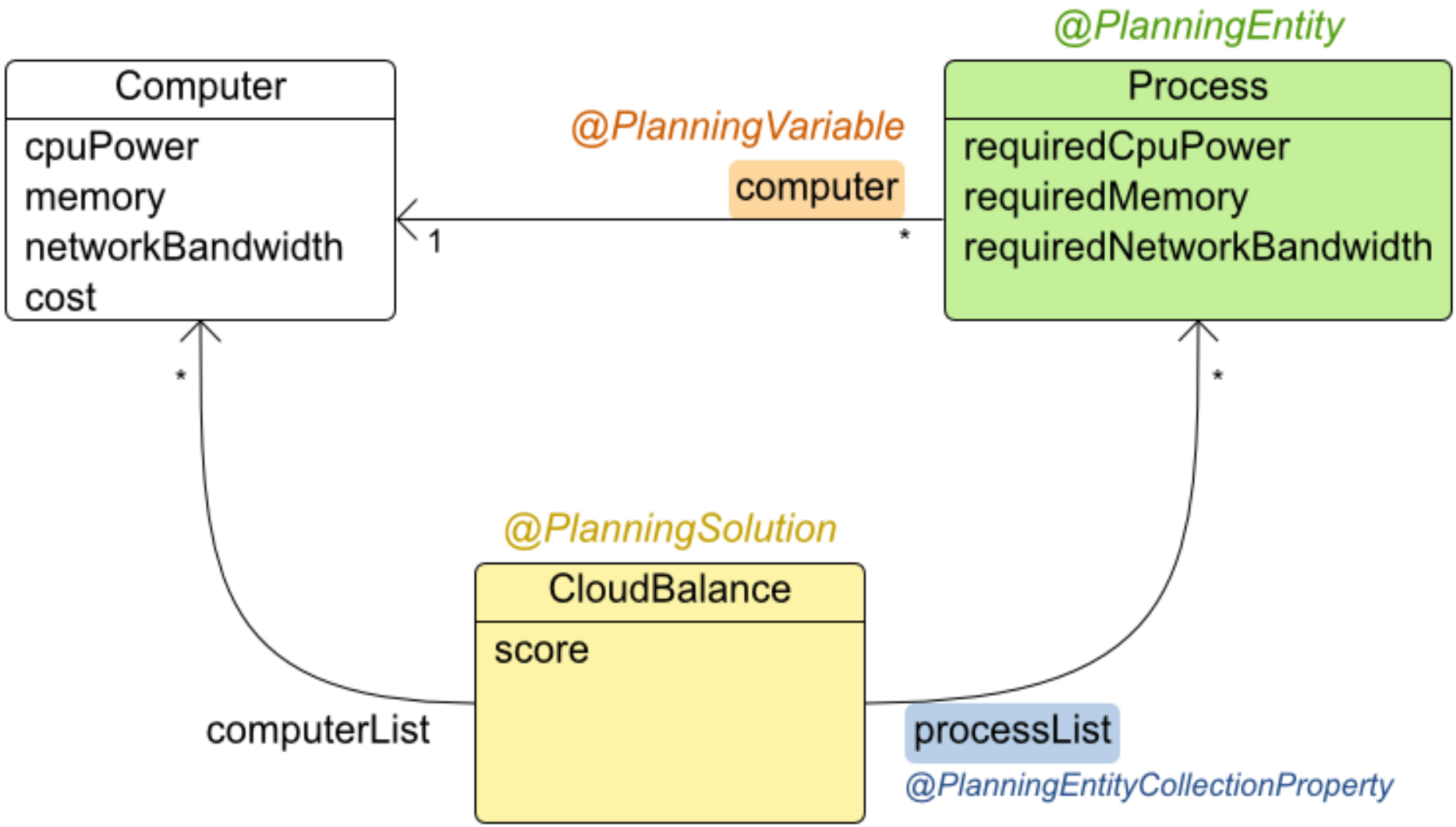
Process is a planning entity

```
@PlanningEntity
public class Process {

  private int requiredCpuPower;
  private int requiredMemory;
  private int requiredNetworkBandwidth;

  // getters

  ...
}
```

Process has a planning variable

```
@PlanningEntity
public class Process {
  ...

  private Computer computer;

  @PlanningVariable(valueRangeProviderRefs = {"computerRange"})
  public Computer getComputer() {
    return computer;
  }
  public void setComputer(Computer computer) {
    this.computer = computer;
  }

}
```

Cloud balance class diagram



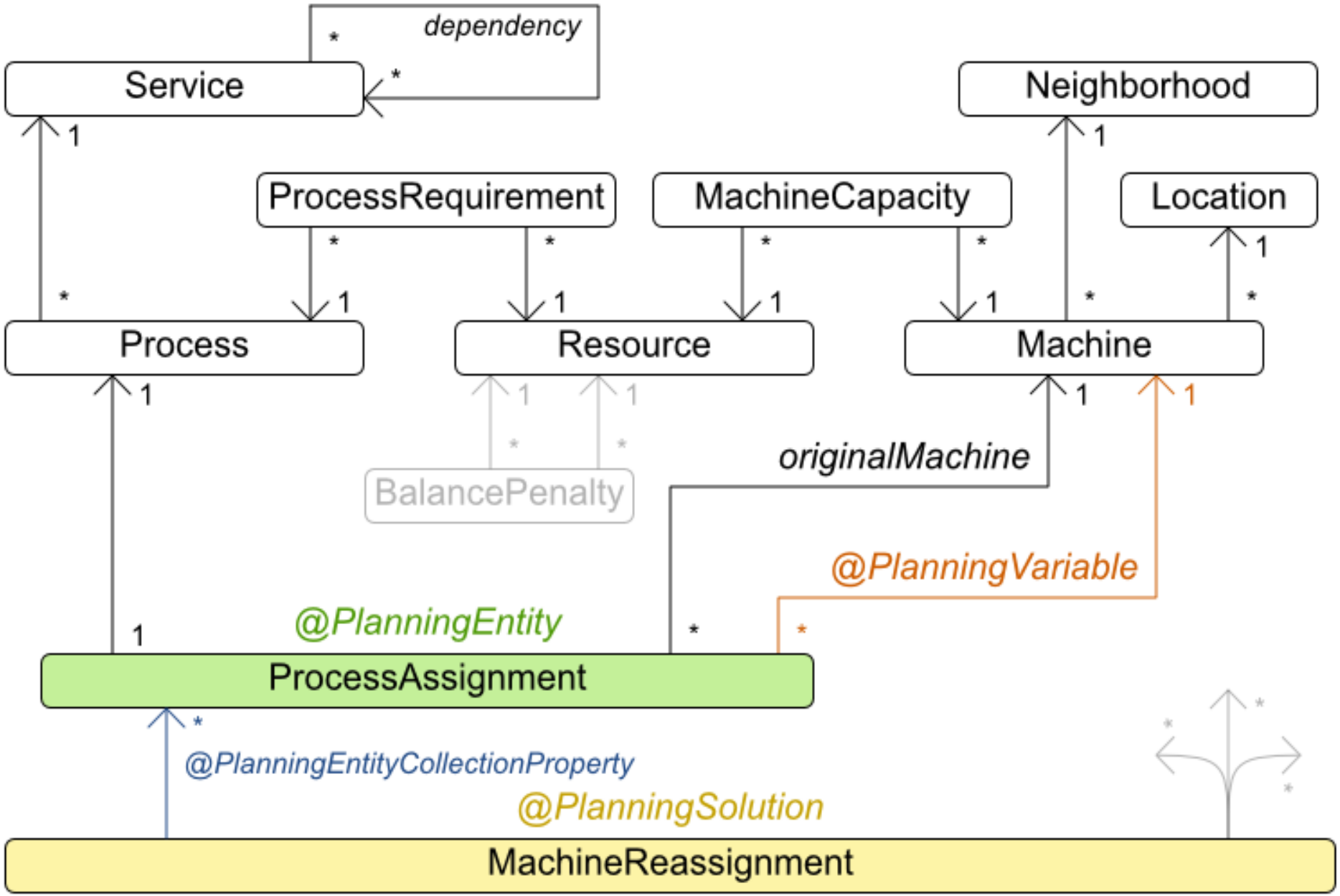
Solution CloudBalance

```
@PlanningSolution
public class CloudBalance implements Solution<HardSoftScore> {

  private List<Computer> computerList;
  private List<Process> processList;

  @ValueRangeProvider(id = "computerRange")
  public List<Computer> getComputerList() {
    return computerList;
  }

  @PlanningEntityCollectionProperty
  public List<Process> getProcessList() {
    return processList;
  }

  ...
`
```

Solution CloudBalance: score

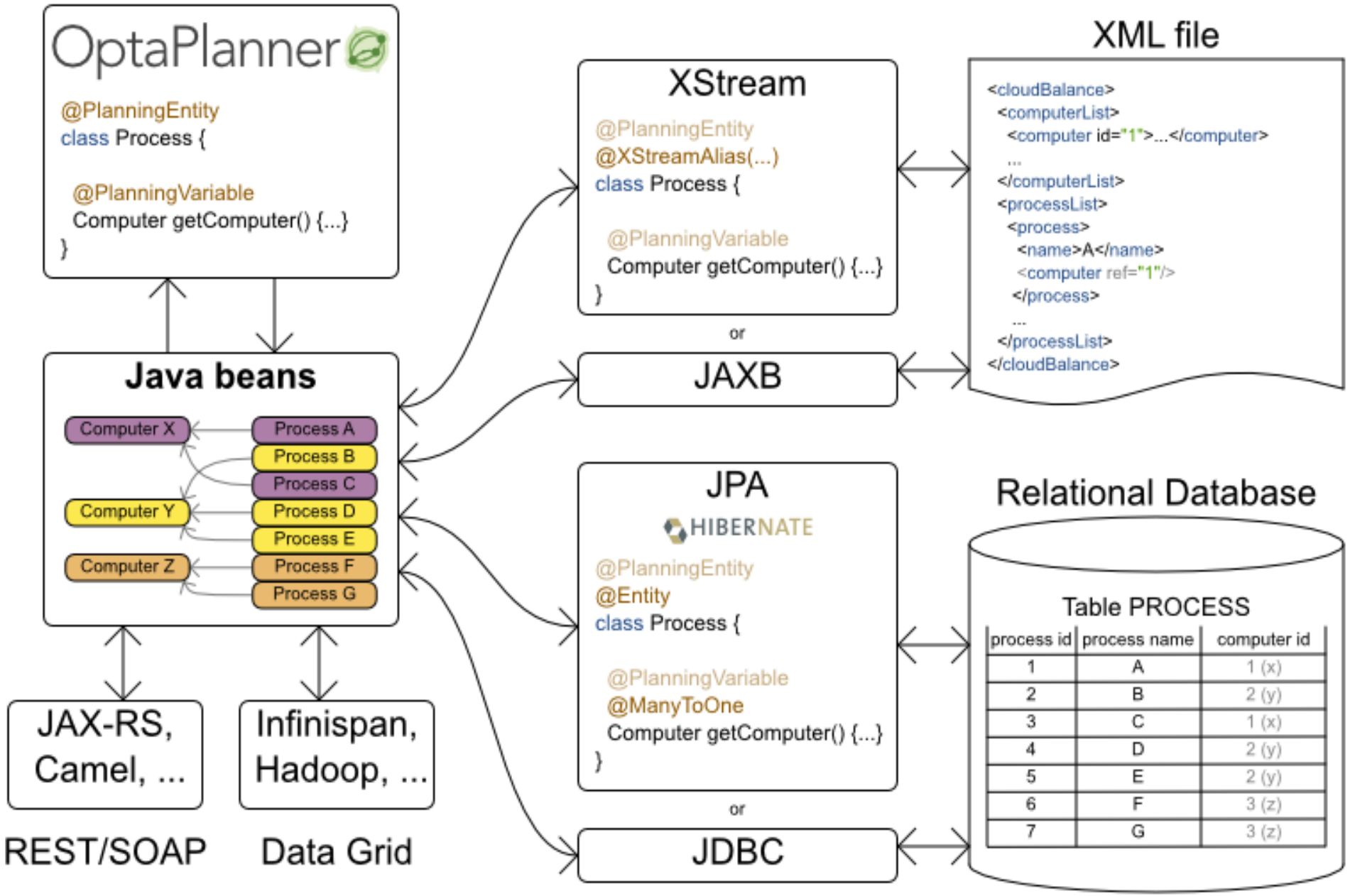
```
public class CloudBalance implements Solution<HardSoftScore> {
  ...

  private HardSoftScore score;

  public HardSoftScore getScore() {
    return score;
  }
  public void setScore(HardSoftScore score) {
    this.score = score;
  }

}
```

Machine reassignment class diagram



Integration overview

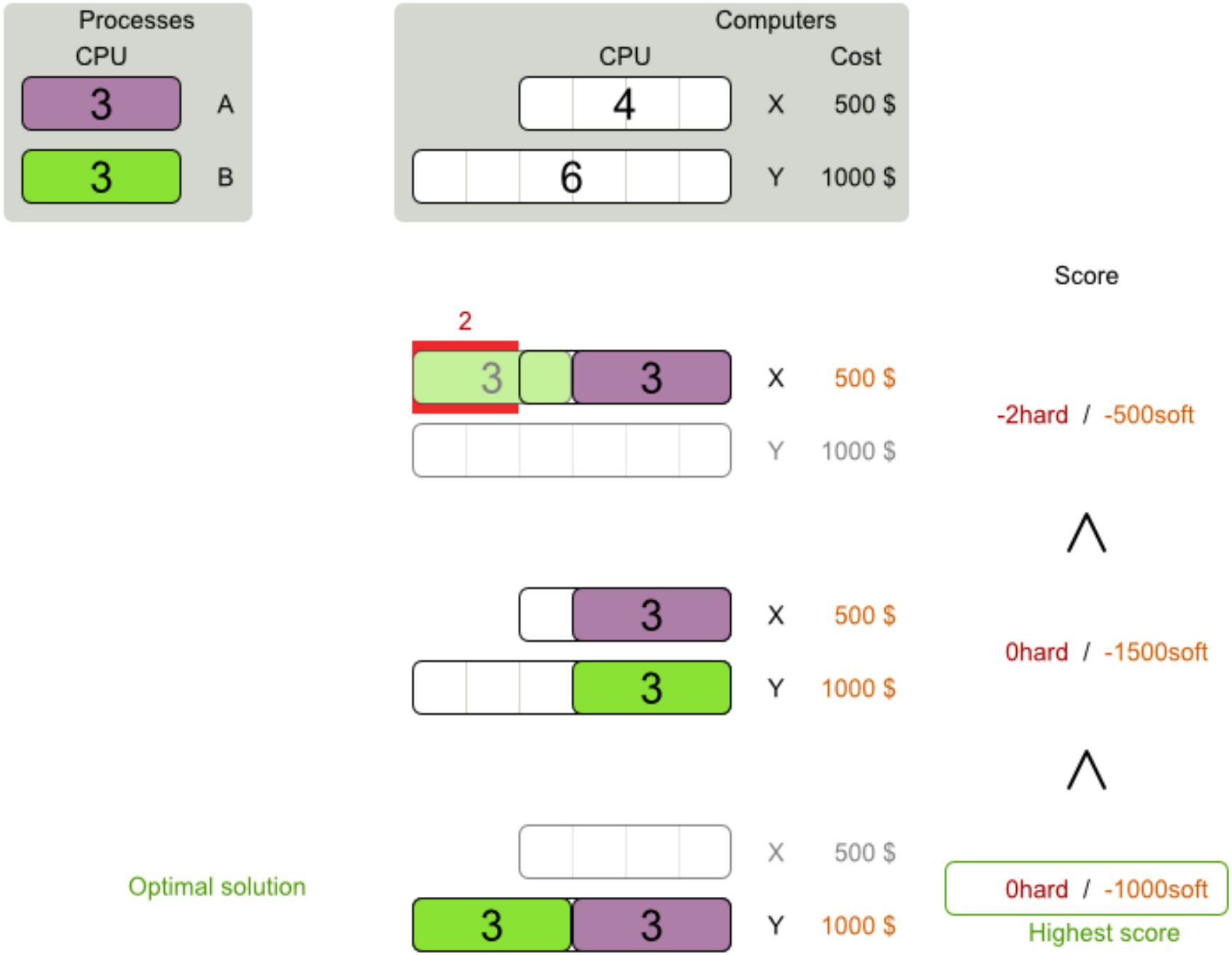
OptaPlanner combines easily with other Java and JEE technologies.



Cloud Balancing example

Score constraints

Given 2 solutions which one is better?


Processes
CPU
3
A
3
B
Computers
CPU
Cost
4
X
500 $
6
Y
1000 $
Score
2
3
3
X
500 $
Y
1000 $
-2hard / -500soft
3
X
500 $
3
Y
1000 $
0hard / -1500soft
X
500 $
3
3
Y
1000 $
0hard / -1000soft
Highest score
Optimal solution

Score calculation

- Easy Java
- Incremental Java
- Drools

Easy Java score calculation

- Easy to implement
- Bridge an existing system
- Slow

```
public class CloudBalancingEasyScoreCalculator
    implements EasyScoreCalculator<CloudBalance> {

  public Score calculateScore(CloudBalance cb) {
    ...
    return HardSoftScore.valueOf(hardScore, softScore);
  }

}
```

Incremental Java score calculation

- Fast
  - Solution changes ⇒ recalculate score delta only
- Hard to implement
  - Much boilerplate code

Drools score calculation

- Incremental
  - No boilerplate code
- Constraints in Drools Rule Language (DRL)
  - Declarative (like SQL, regular expression)
- Integration opportunities
  - Drools Workbench
  - Decision tables

Solution CloudBalance: getProblemFacts()

```
public class CloudBalance implements Solution<HardSoftScore> {

  private List<Computer> computerList;
  private List<Process> processList;
  ...

  // Used in Drools score rules (DRL)
  public Collection<Object> getProblemFacts() {
    List<Object> facts = new ArrayList<Object>();
    facts.addAll(computerList);
    return facts;
  }

  ...
}
```

DRL soft constraint: computer cost

```
rule "computerCost"
  when
    // there is a computer
    $s : Computer($c : cost)
    // there is a processes on that computer
    exists Process(computer == $s)
  then
    // lower soft score by the maintenance cost
    scoreHolder.addSoftConstraintMatch(kcontext, - $c);
end
```

DRL hard constraint: CPU power

```
rule "requiredCpuPowerTotal"
  when
    // there is a computer
    $s : Computer($cpu : cpuPower)
    // with too little cpu for its processes
    $total : Number(intValue > $cpu) from accumulate(
      Process(computer == $s, $requiredCpu : requiredCpuPower),
      sum($requiredCpu)
    )
  then
    // lower hard score by the excessive CPU usage
    scoreHolder.addHardConstraintMatch(kcontext,
        $cpu - $total.intValue());
end
```

Score calculation must be flexible

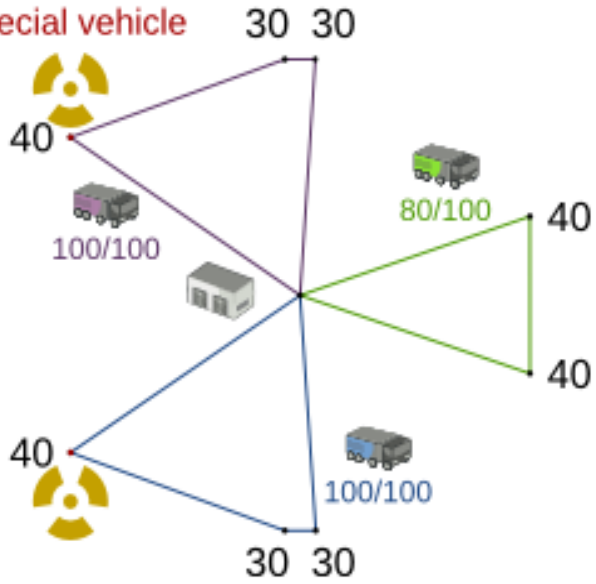
- **Optimal solution for *almost* your business problem is useless**
- Model supports:
  - Reusing existing classes
  - Rich, OO class hierarchies (including polymorphism)
- Constraints supports:
  - Any constraint (no linear or quadratic restrictions!)
  - Reusing existing code
- Scoring supports:
  - Positive/negative mix
  - Score weights
  - Unlimited score levels

Optimal with incomplete constraints

The optimal solution for a problem that misses a constraint is probably useless.

Optimal solution
with missing constraint

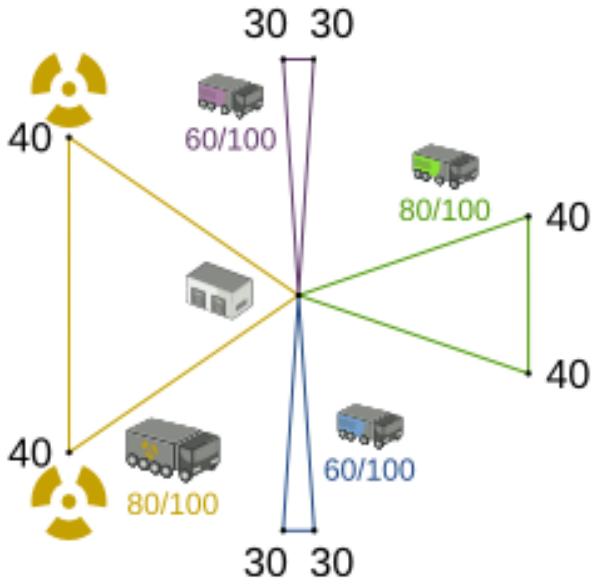
Nuclear cargo requires
special vehicle



-283

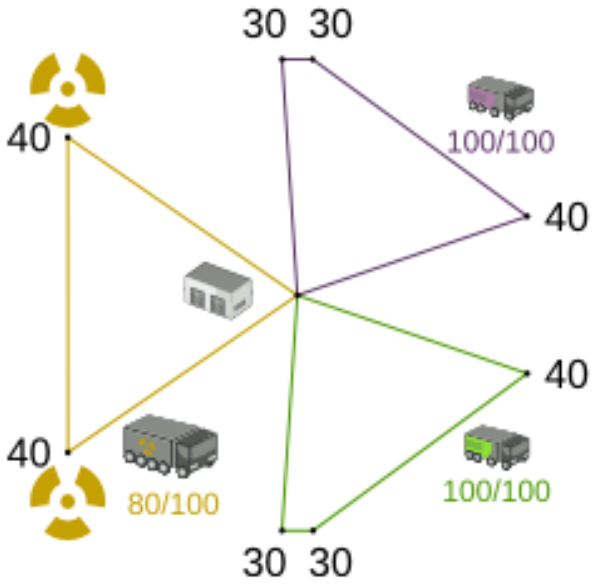
Not feasible

Patched solution
for missing constraint



-324

Optimal solution
with all constraints



-312

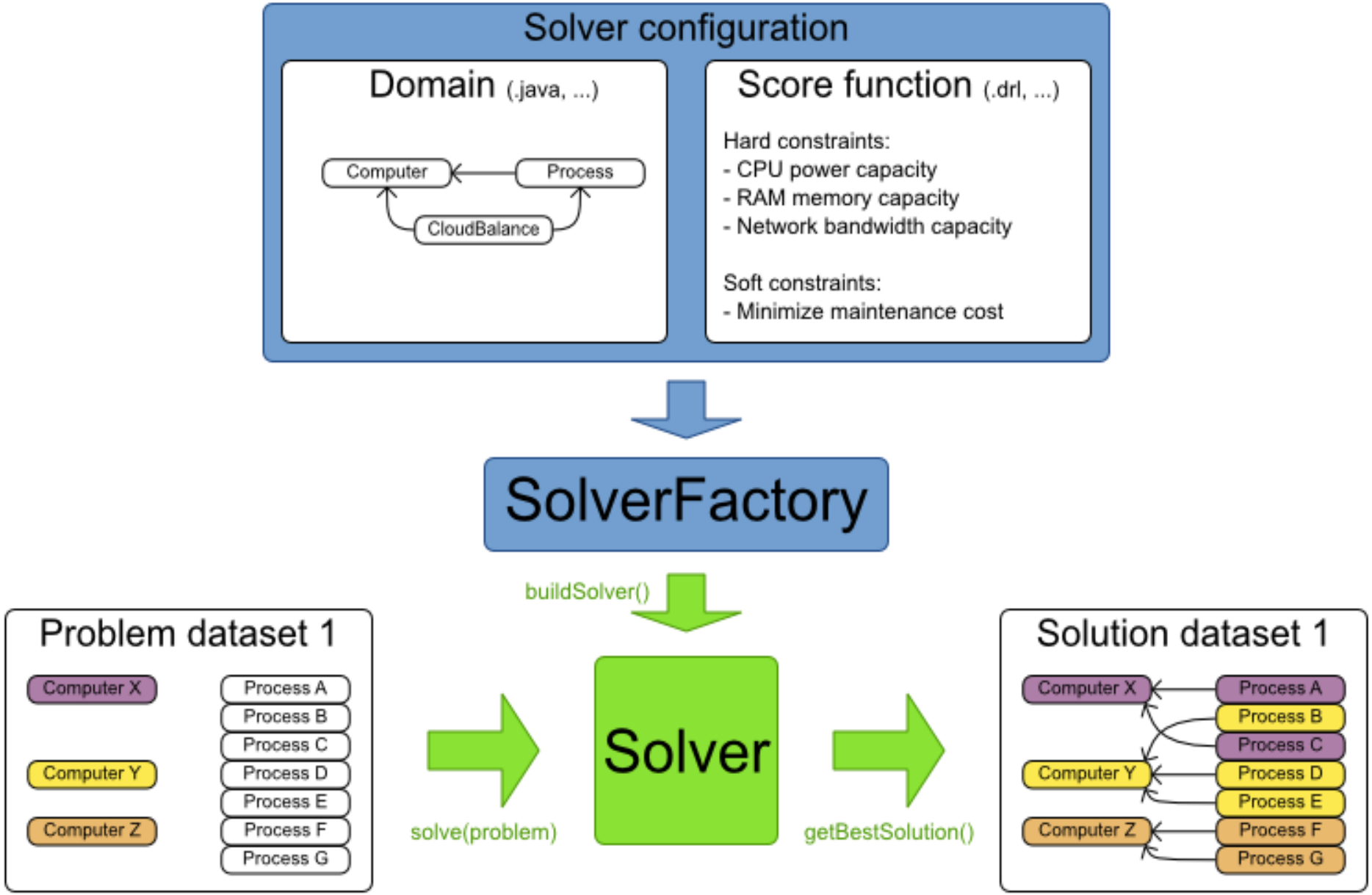
Highest feasible score

Cloud Balancing example

Solving it

Input/Output overview

Use 1 SolverFactory per application and 1 Solver per dataset.



Solver configuration by XML

```
<solver>
  <solutionClass>...CloudBalance</solutionClass>
  <entityClass>...Process</entityClass>

  <scoreDirectorFactory>
    <scoreDefinitionType>HARD_AND_SOFT</scoreDefinitionType>
    <scoreDrl>...ScoreRules.drl</scoreDrl>
  </scoreDirectorFactory>

  <!-- optimization algorithms -->
</solver>
```

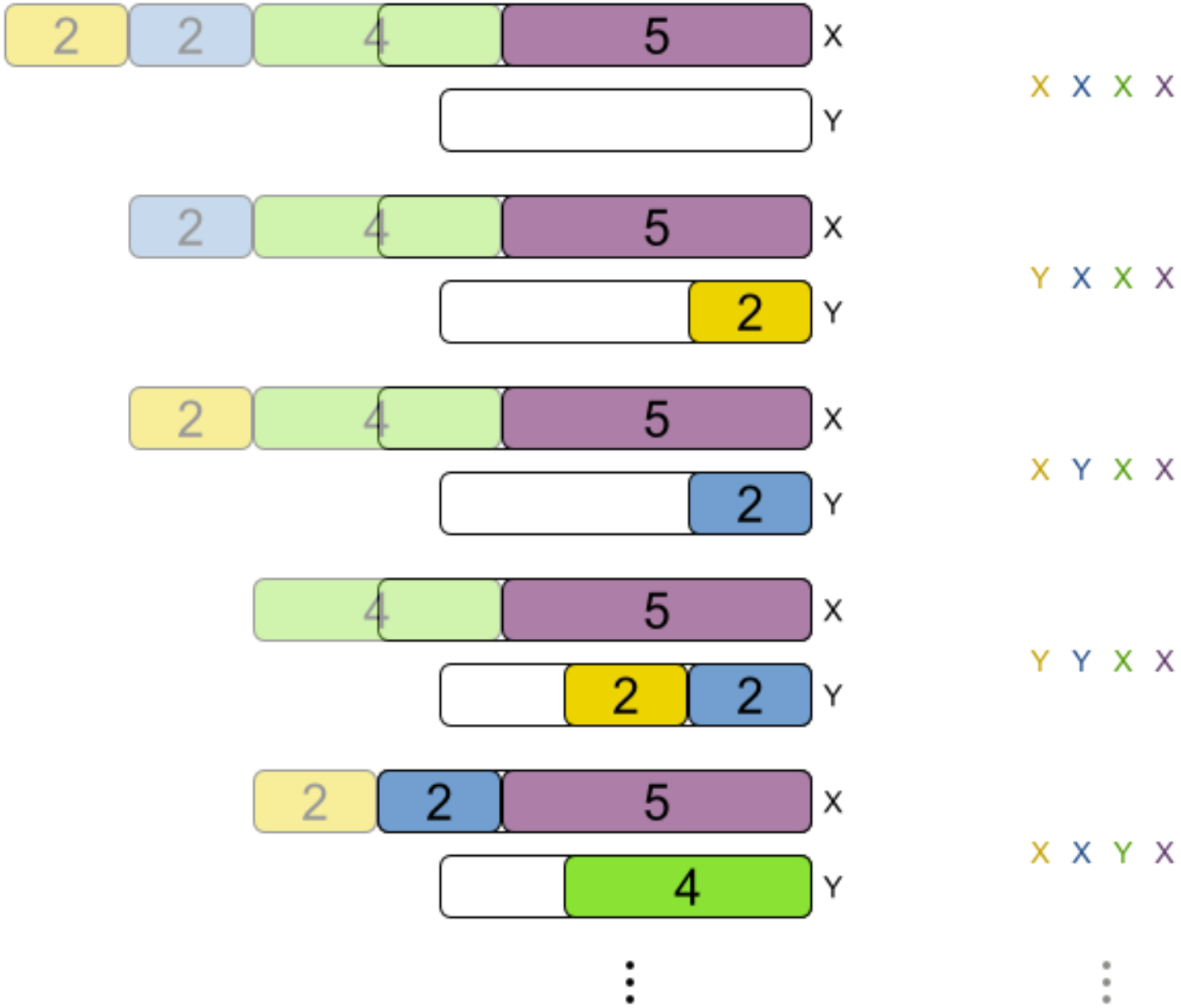
Solving

```
SolverFactory factory = SolverFactory.createFromXmlResource(
    "...SolverConfig.xml");
Solver solver = factory.buildSolver();

solver.solve(cloudBalance);
cloudBalance = (CloudBalance) solver.getBestSolution();
```

Cloud Balancing example

Optimization algorithms

Brute Force

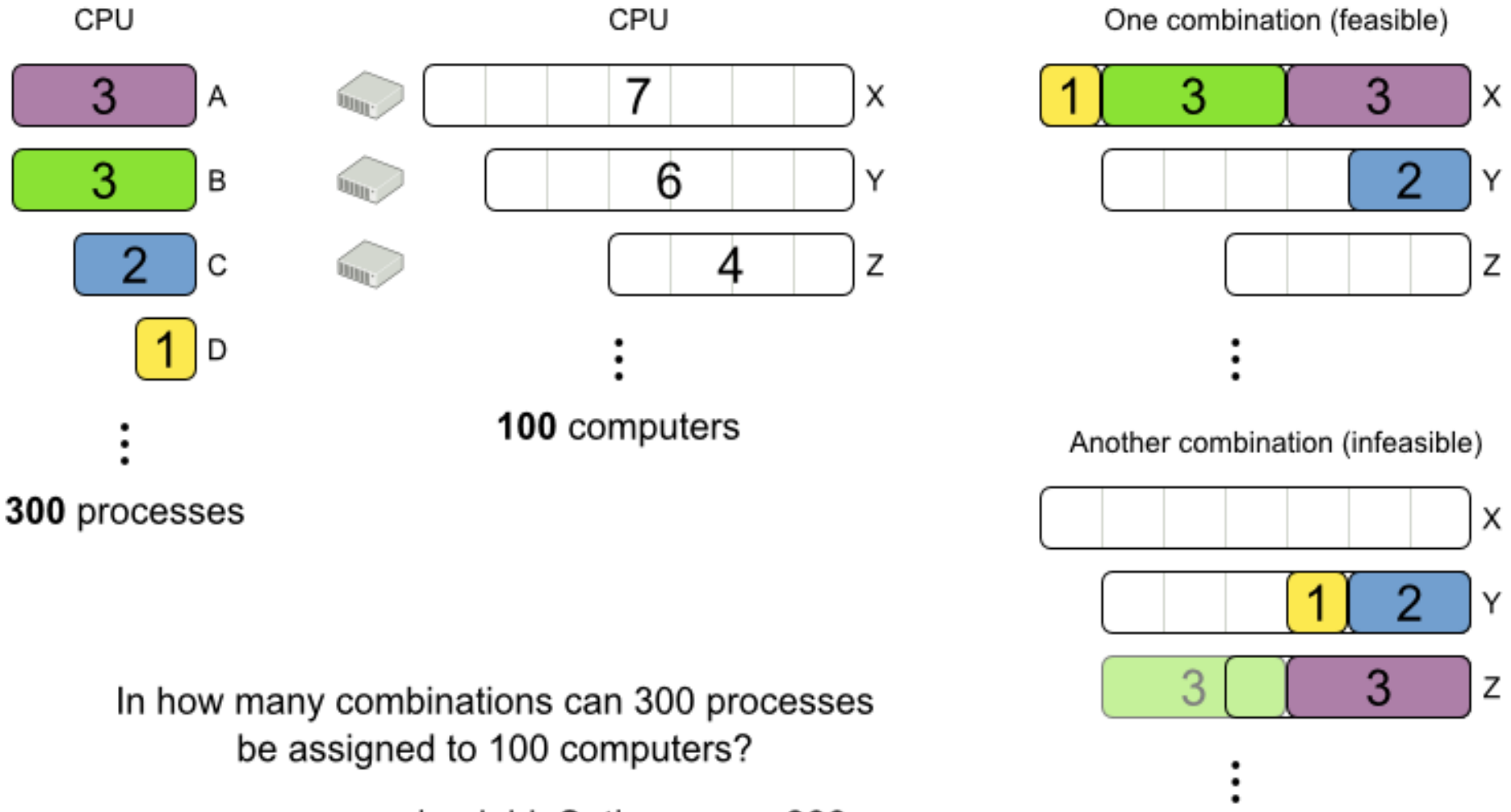

2
2
4
5
X
Y
2
4
5
X
2
Y
2
4
5
X
2
Y
4
5
X
2
2
Y
2
2
5
X
4
Y
X X X X
Y X X X
X Y X X
Y Y X X
X X Y X

Brute Force config

```
<solver>
  ...

  <exhaustiveSearch>
    <exhaustiveSearchType>BRUTE_FORCE</exhaustiveSearchType>
  </exhaustiveSearch>
</solver>
```

What is the size of the search space?

How big is the haystack?

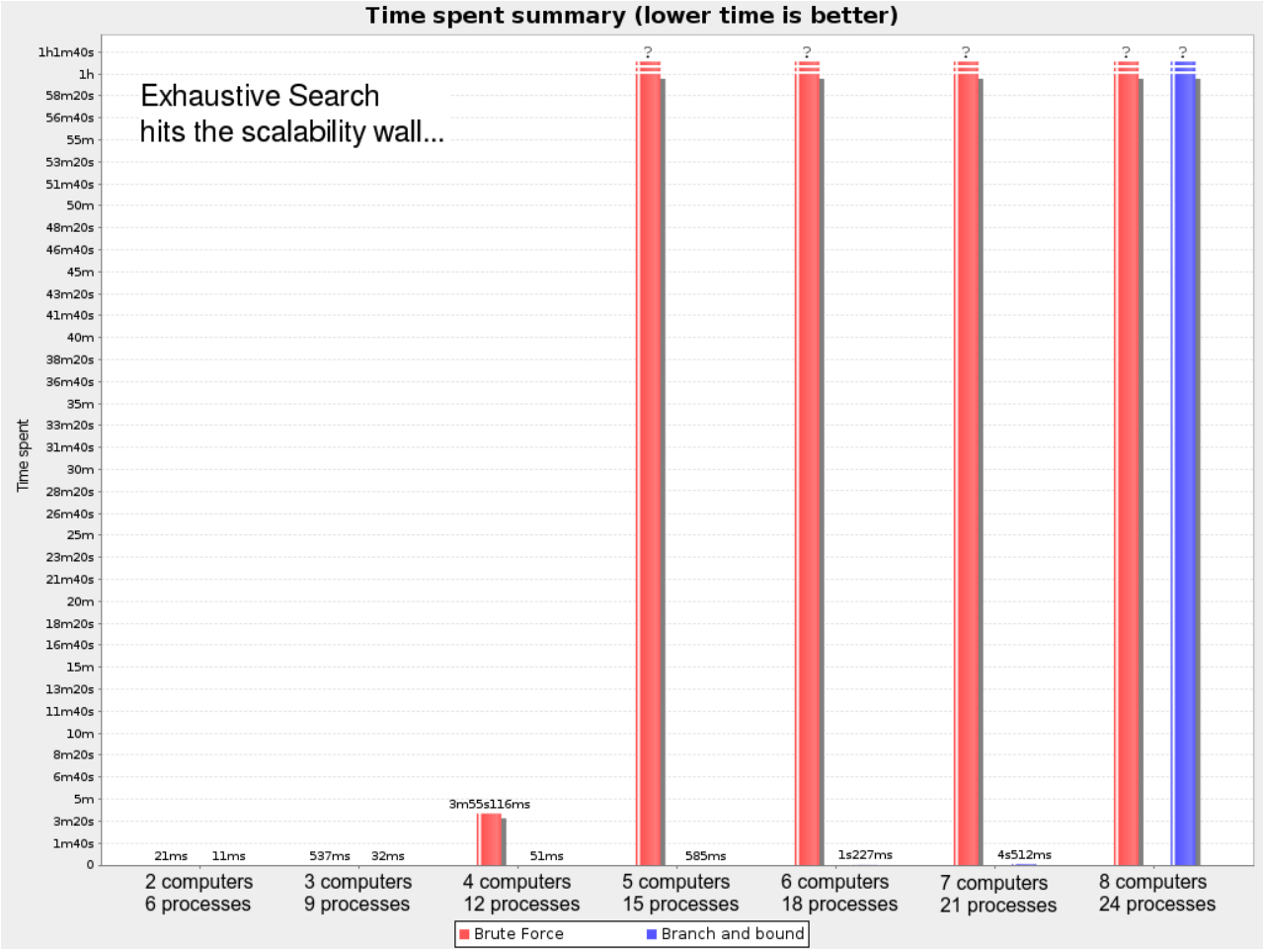


In how many combinations can 300 processes be assigned to 100 computers?

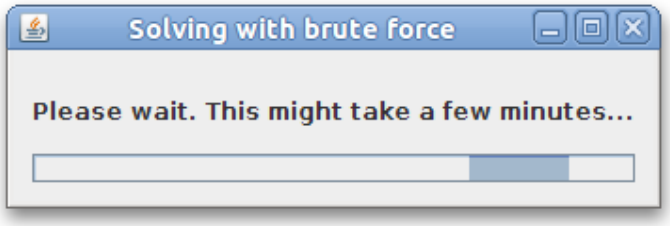
$$|\text{valueSet}|^{|\text{variableSet}|} = \mathbf{100^{300}}$$

$$= 10^{600} = 1000000000000000000000...$$

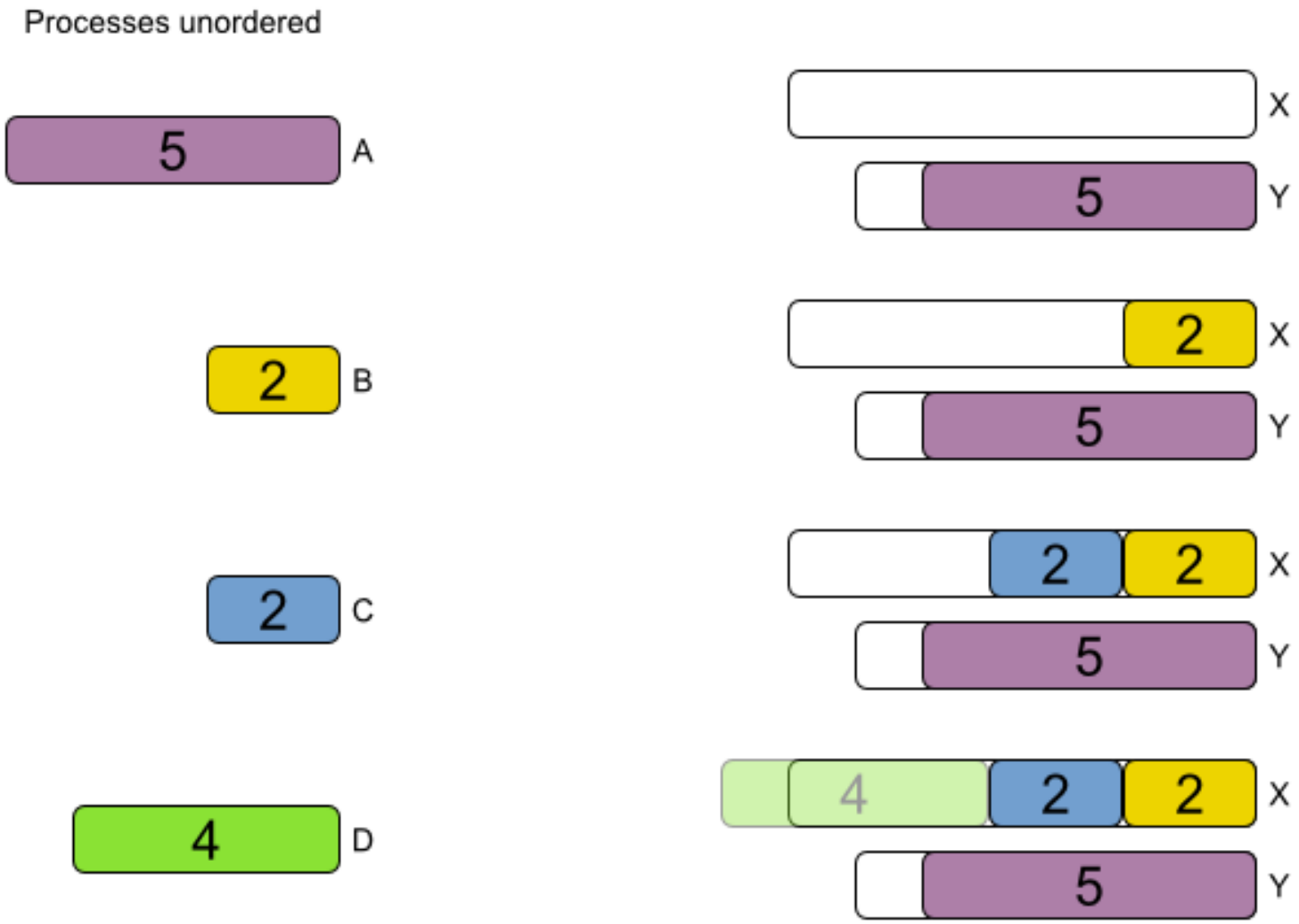
Brute Force scalability



Plan 1200 processes with Brute Force?



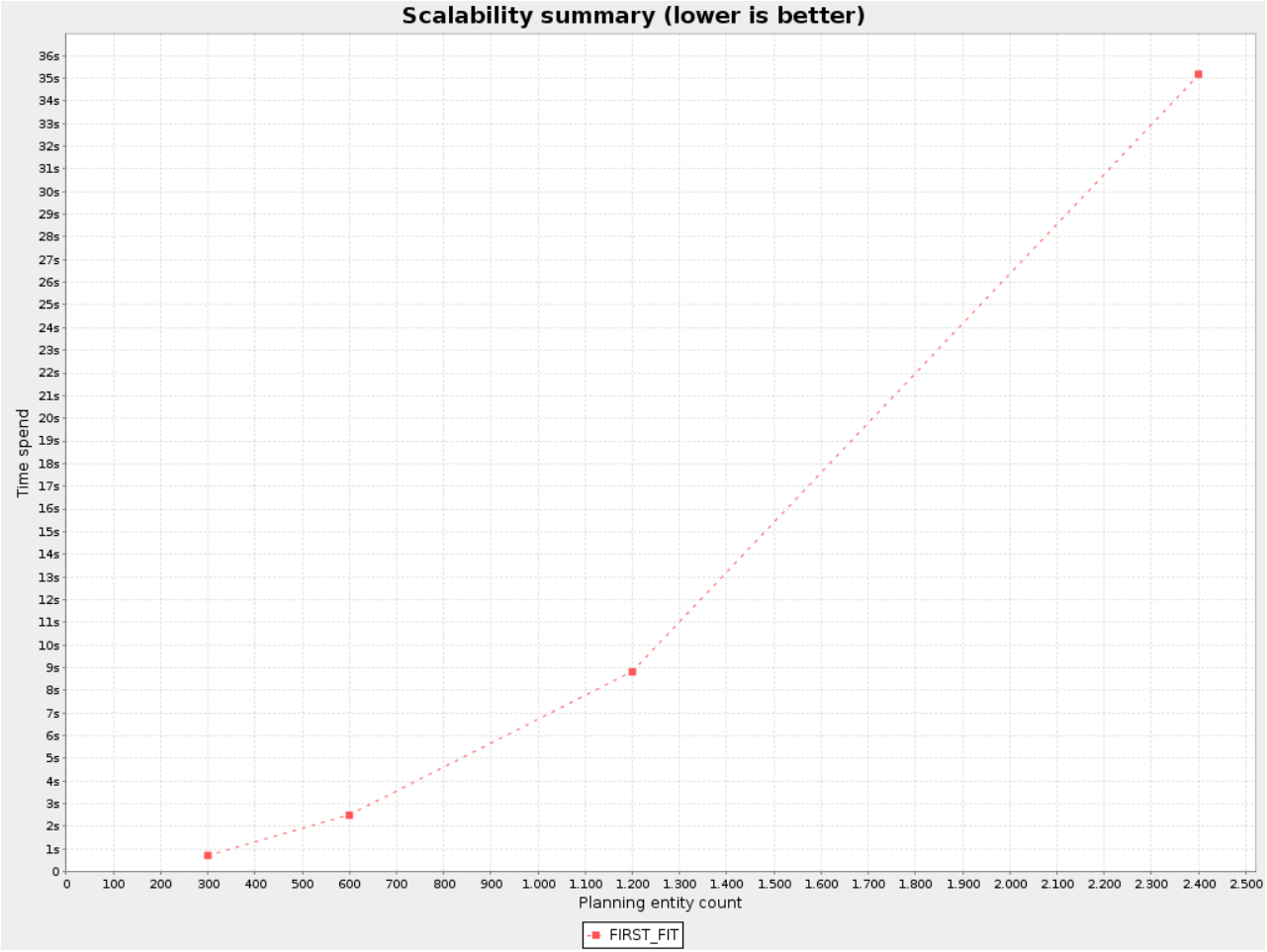
First Fit



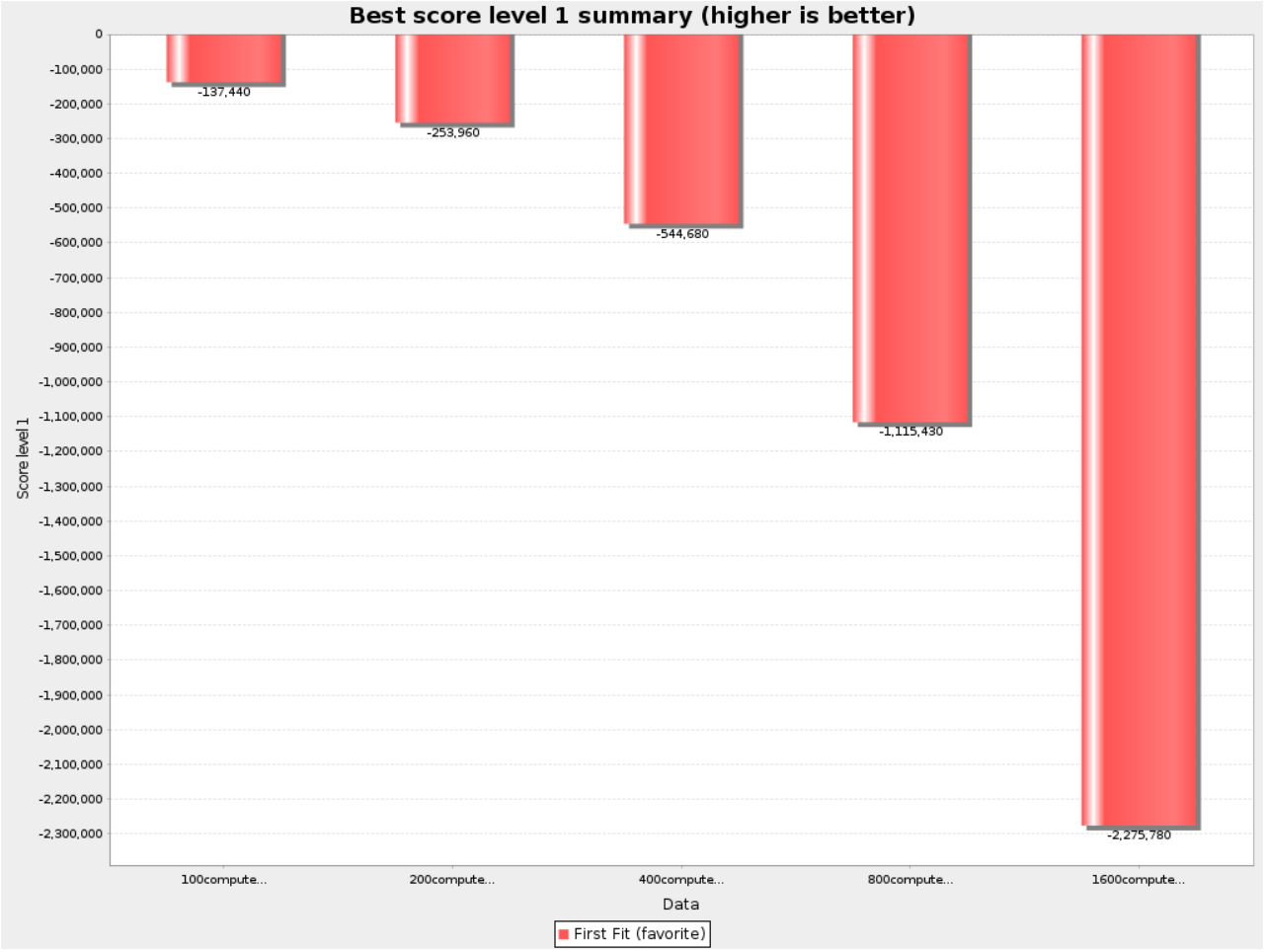
First Fit config

```
<solver>
  ...

  <constructionHeuristic>
    <constructionHeuristicType>FIRST_FIT</constructionHeuristicType>
  </constructionHeuristic>
</solver>
```

First Fit scalability

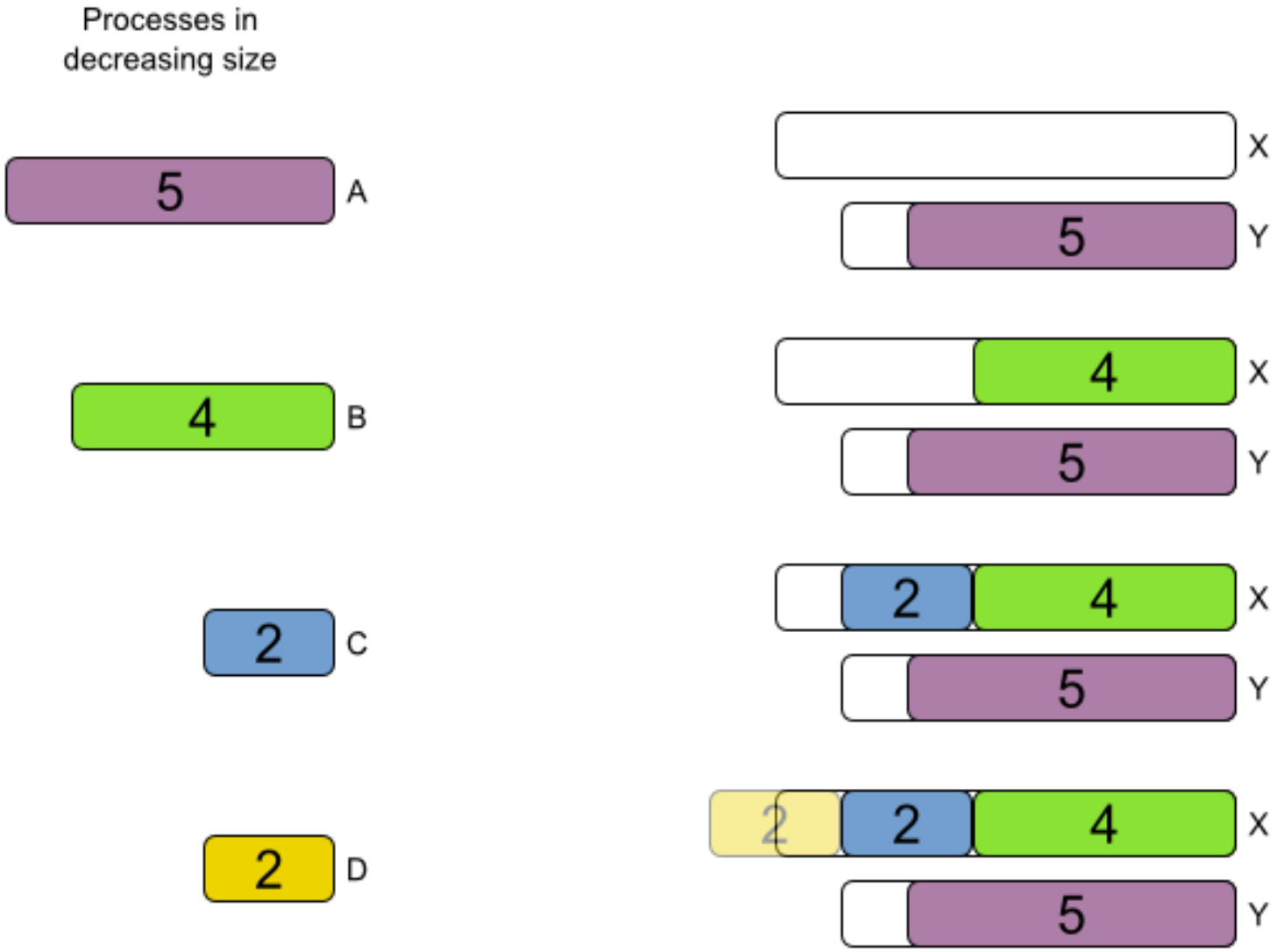


First Fit results



All hard constraints satisfied: maintenance cost shown

First Fit Decreasing



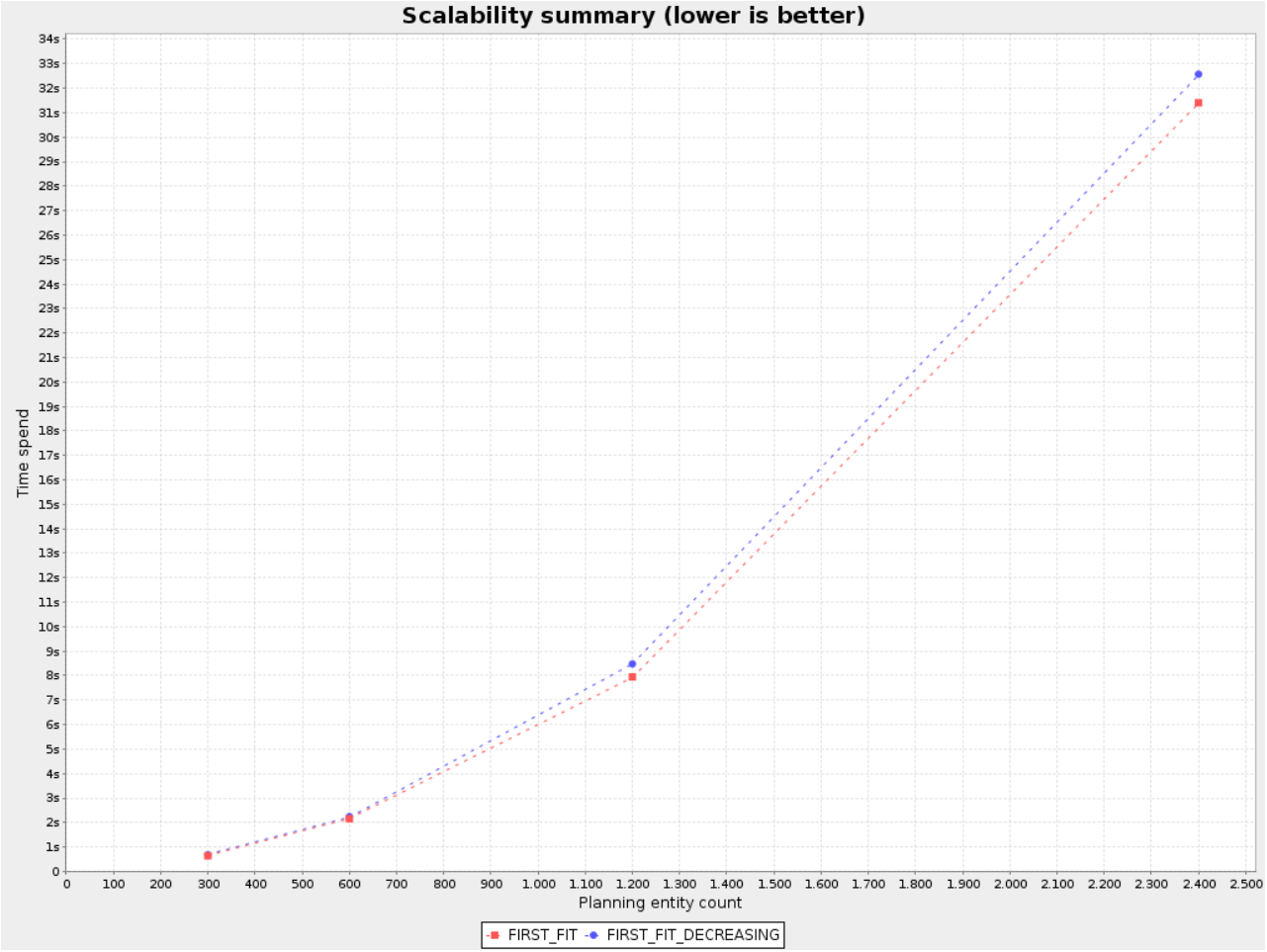
First Fit Decreasing config

```
<solver>
  ...

  <constructionHeuristic>
    <constructionHeuristicType>FIRST_FIT_DECREASING</constructionHeuristicTy
pe>
  </constructionHeuristic>
</solver>
```

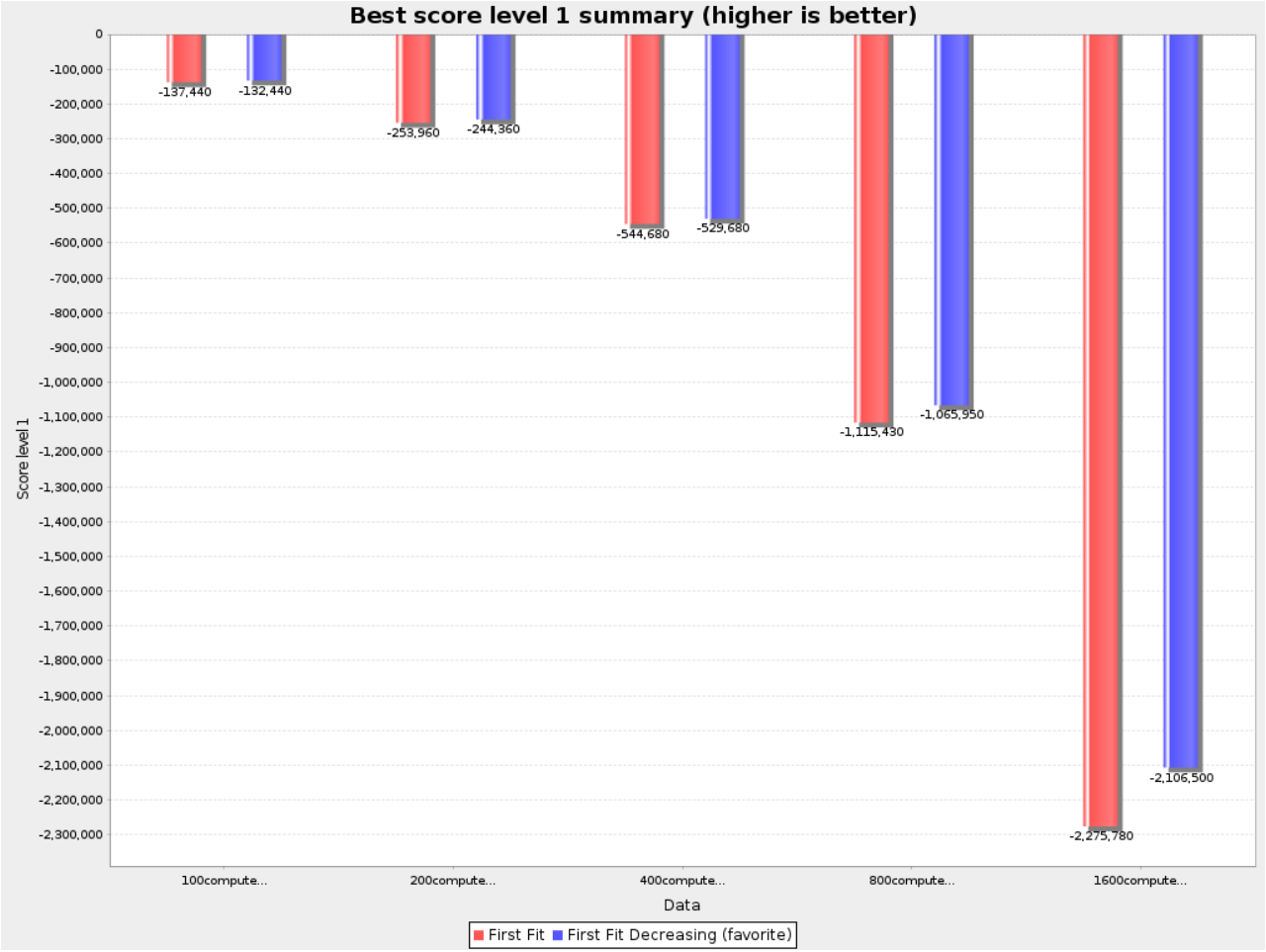
DifficultyComparator

```
public class ProcessDifficultyComparator
    implements Comparator<Process> {
  public int compare(Process a, Process b) {
    // Compare on requiredCpuPower * requiredMemory
    //     * requiredNetworkBandwidth
  }
}

@PlanningEntity(difficultyComparatorClass
    = ProcessDifficultyComparator.class)
public class Process  {
  ...
}
```

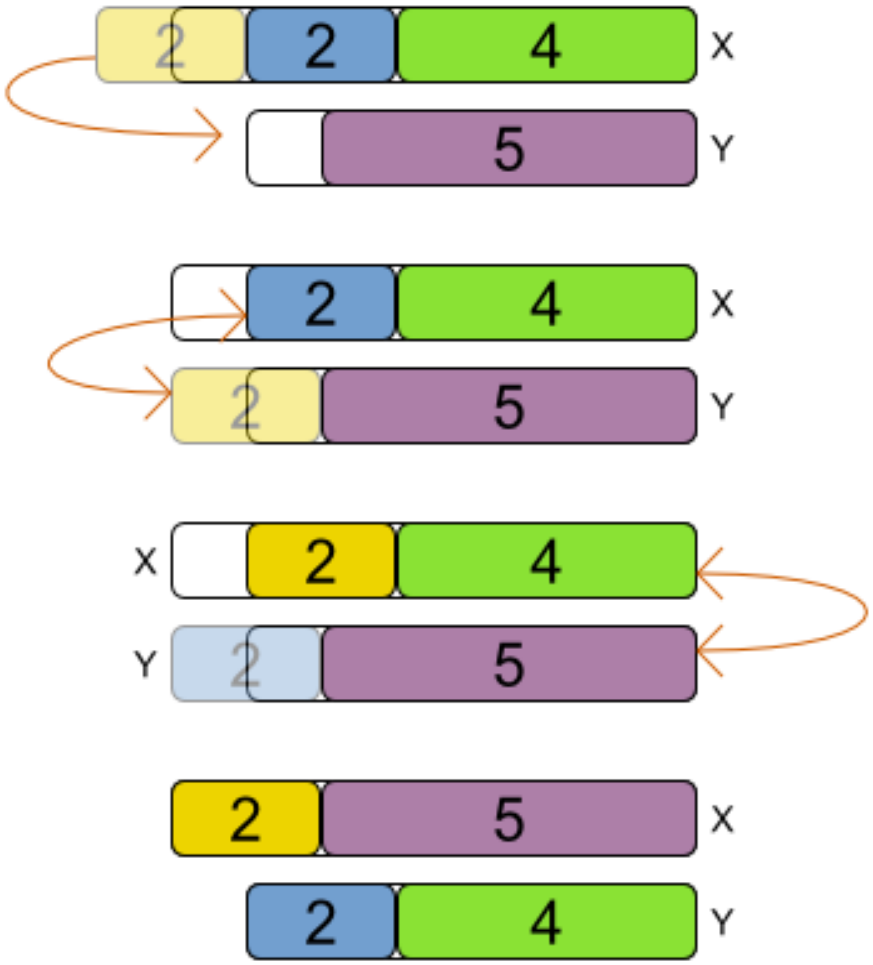
First Fit Decreasing scalability



First Fit Decreasing results

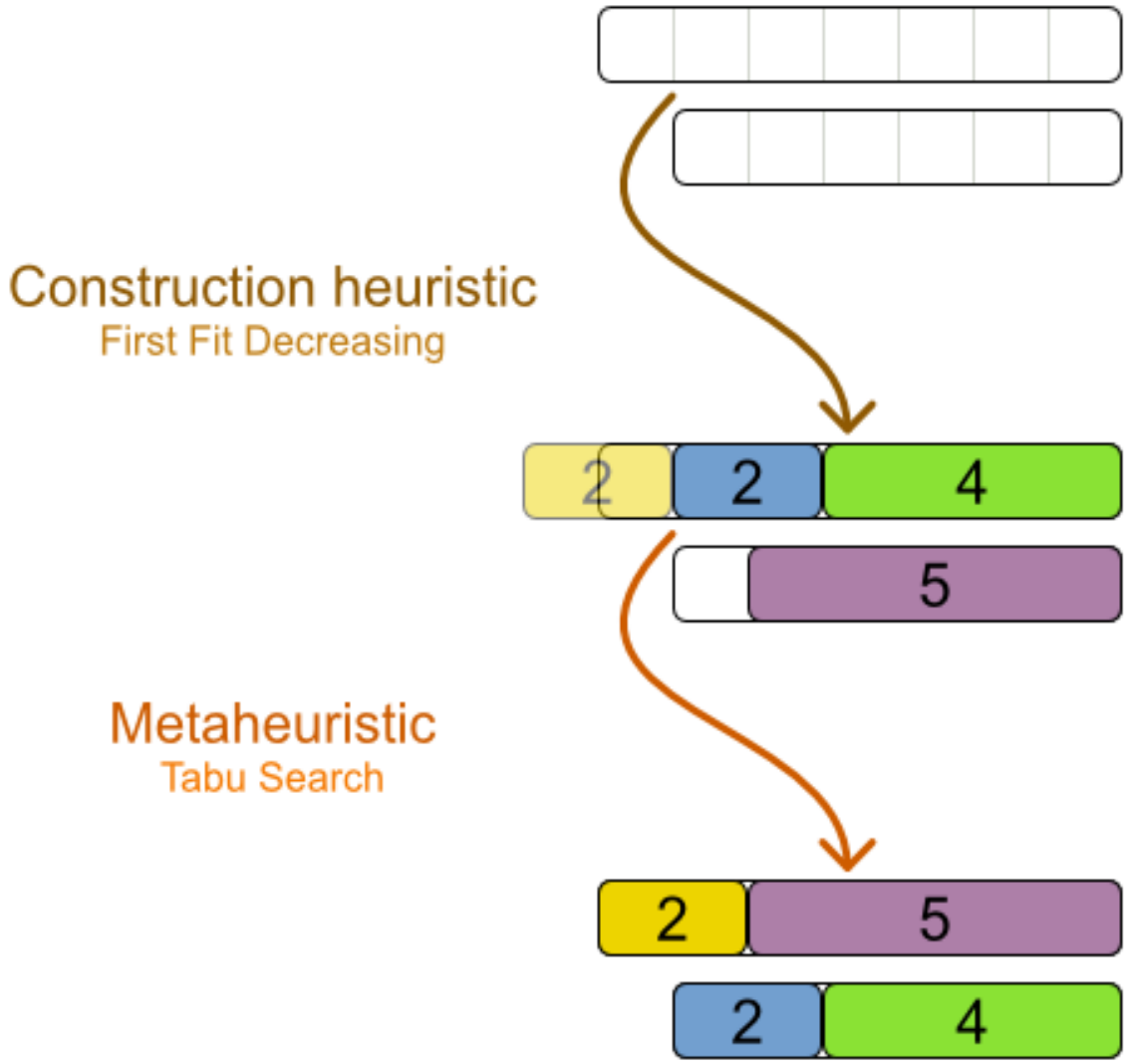


Local Search



General phase sequence

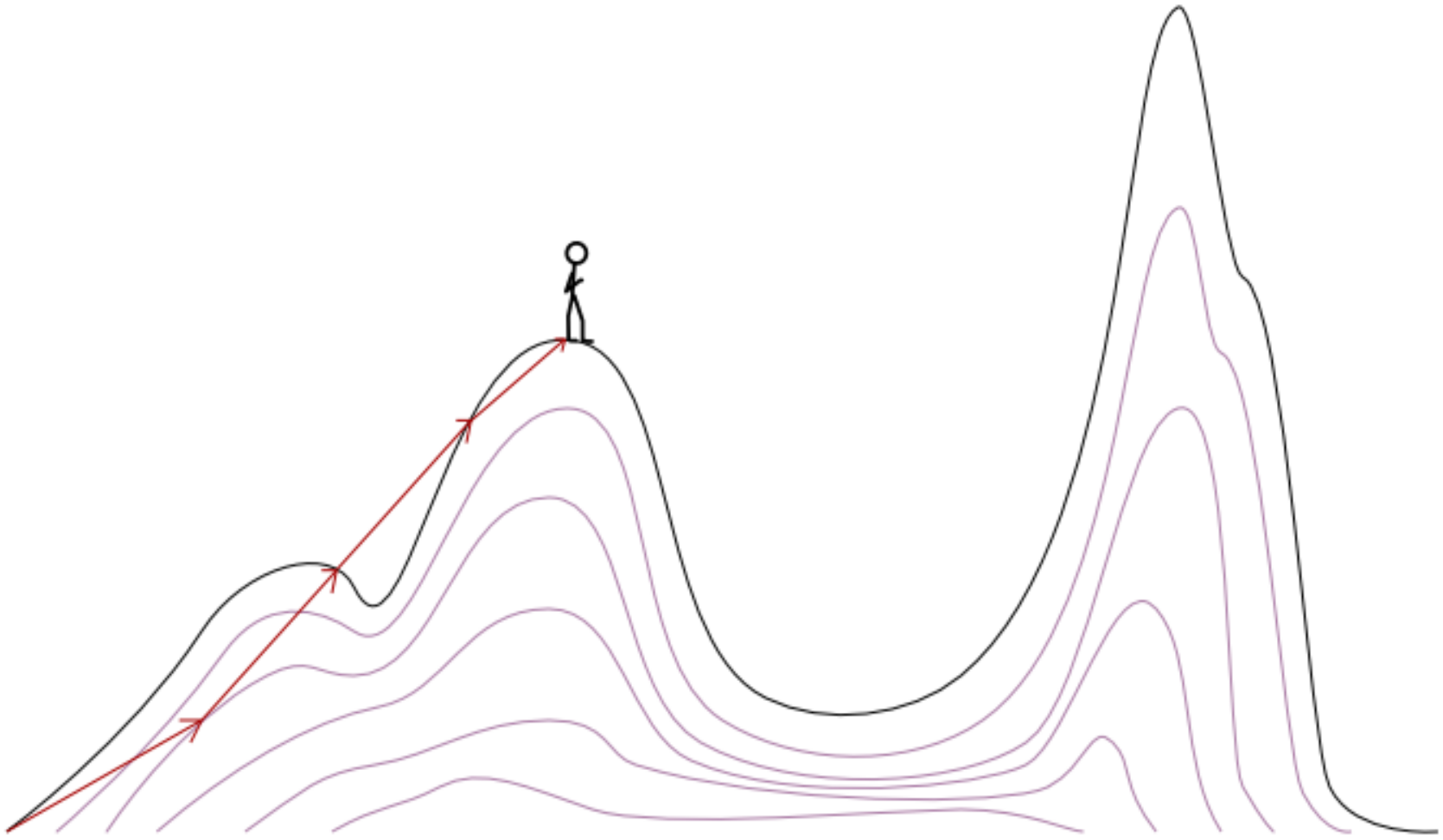
First a construction heuristic,
then metaheuristics



Construction Heuristics + Local Search

```
<solver>
  ...

  <constructionHeuristic>
    <constructionHeuristicType>FIRST_FIT_DECREASING</constructionHeuristicTy
pe>
  </constructionHeuristic>
  <localSearch>
    ...
  <localSearch>
</solver>
```

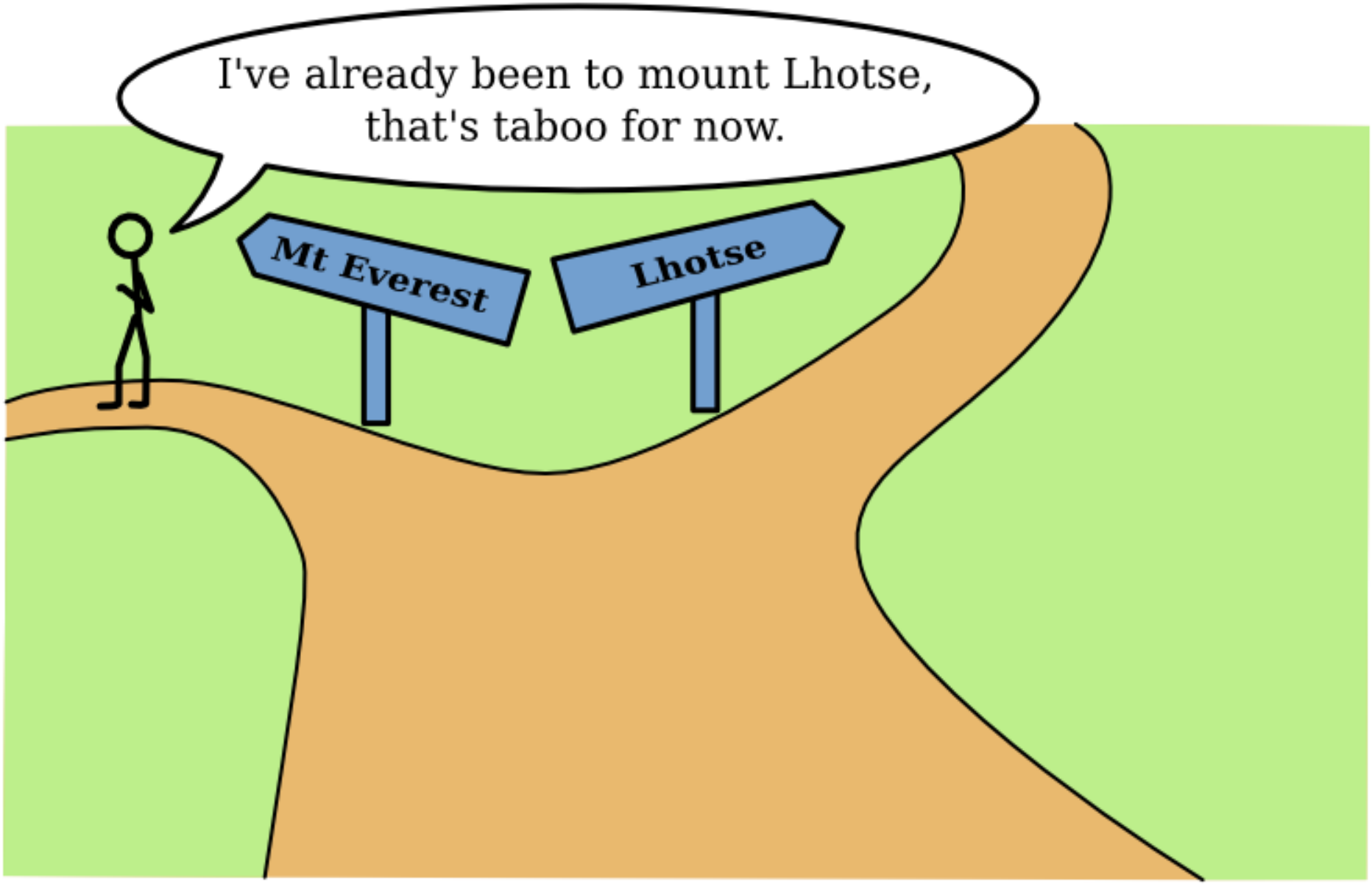
Hill climbing



Hill Climbing config

```
<localSearch>
  <forager>
    <!-- Untweaked standard value -->
    <acceptedCountLimit>1000</acceptedCountLimit>
  </forager>
</localSearch>
```

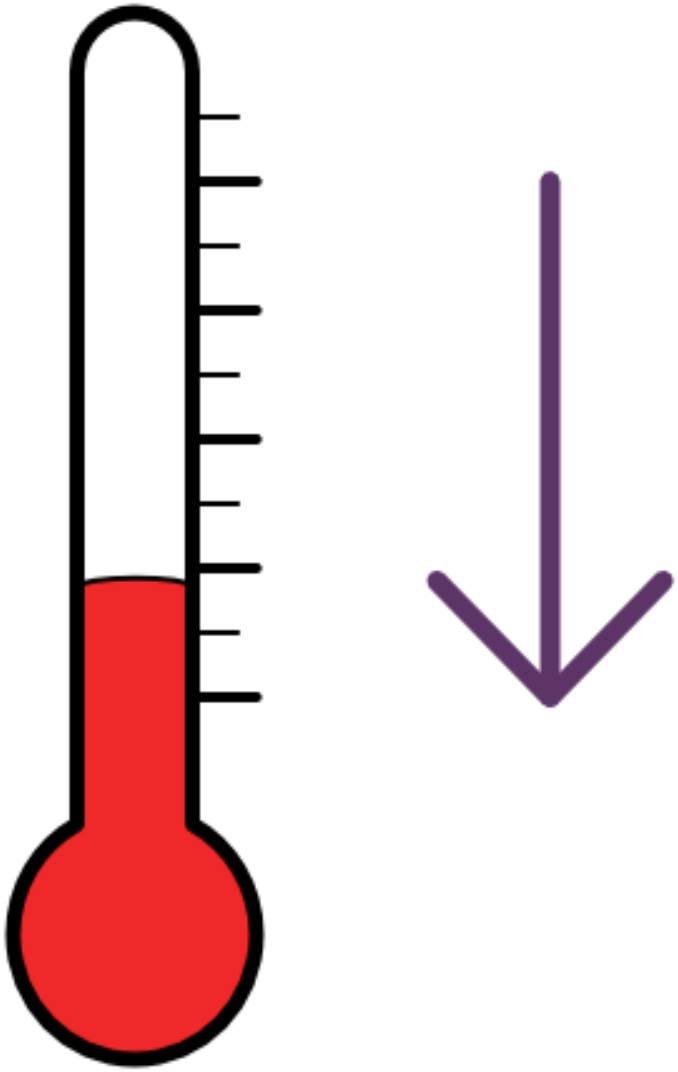
Tabu Search


I've already been to mount Lhotse,
that's taboo for now.
Mt Everest
Lhotse

Tabu Search config

```
<localSearch>
  <acceptor>
    <!-- Typical standard value -->
    <entityTabuSize>7</entityTabuSize>
  </acceptor>
  <forager>
    <!-- Typical value -->
    <acceptedCountLimit>1000</acceptedCountLimit>
  </forager>
</localSearch>
```

Simulated Annealing



Simulated Annealing config

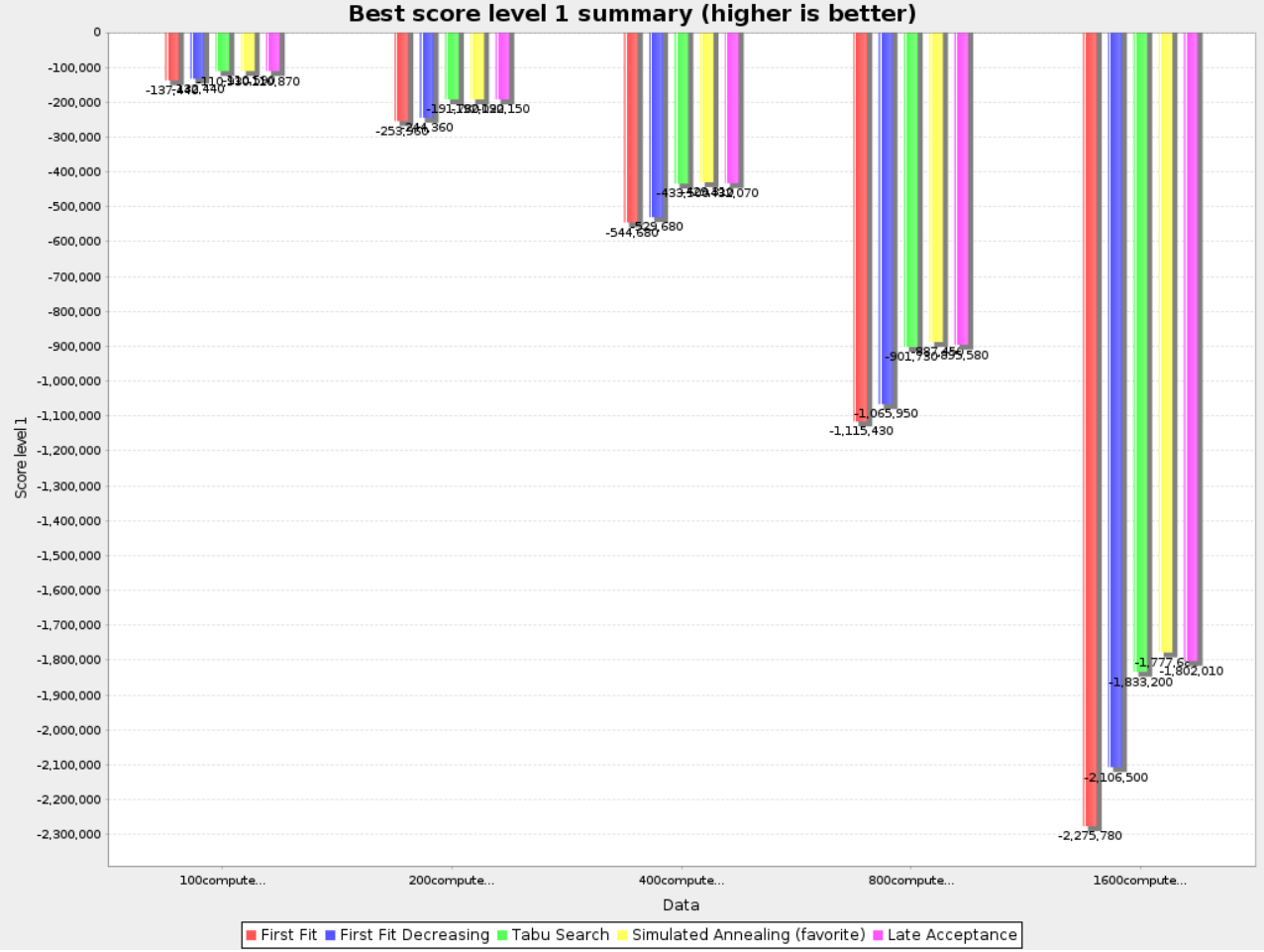
```
<localSearch>
  <acceptor>
    <!-- Tweaked value -->
    <simulatedAnnealingStartingTemperature>
        0hard/400soft
    </simulatedAnnealingStartingTemperature>
  </acceptor>
  <forager>
    <!-- Typical value -->
    <acceptedCountLimit>4</acceptedCountLimit>
  </forager>
</localSearch>
```

Late acceptance

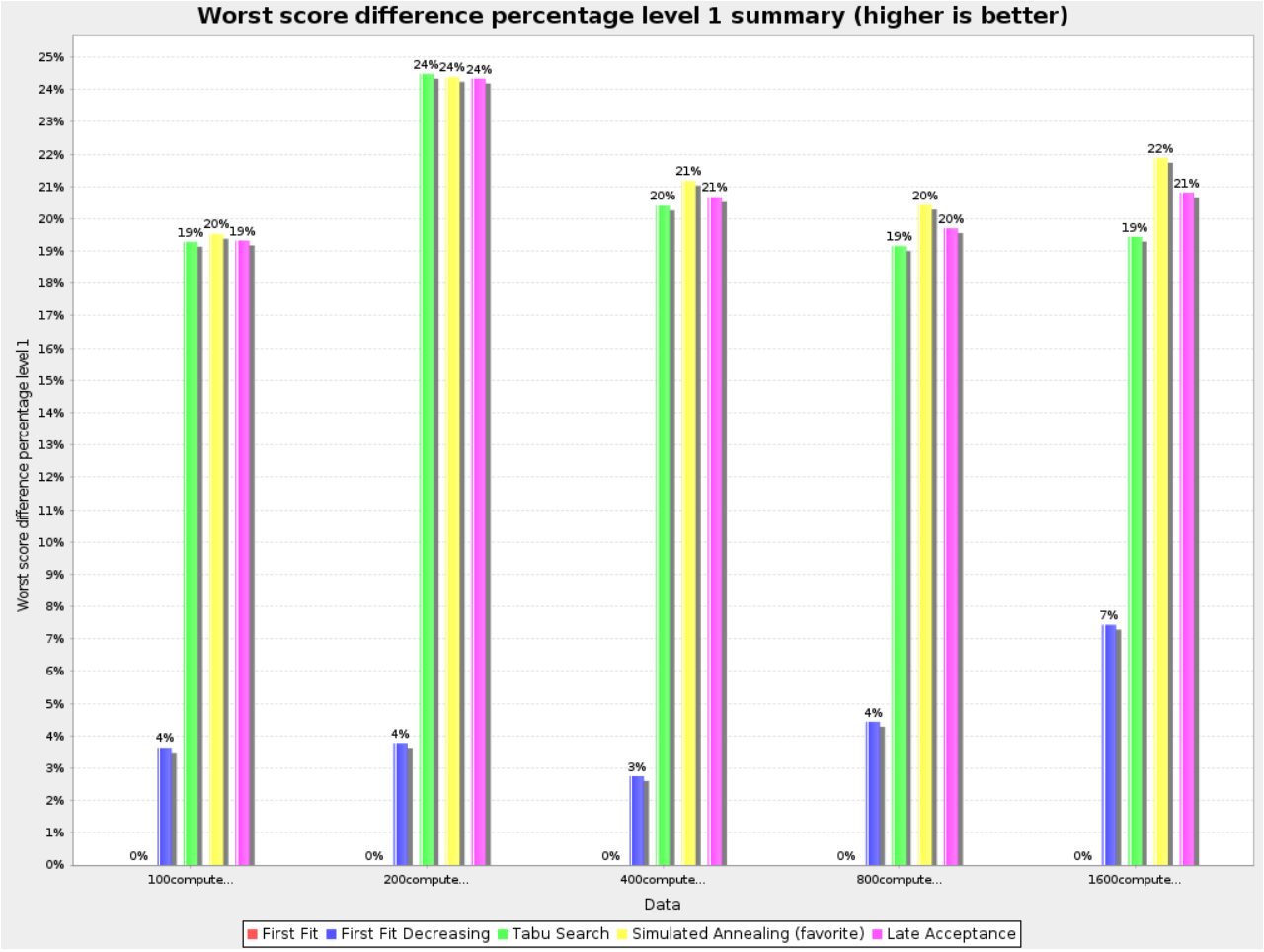
Late Acceptance config

```
<localSearch>
  <acceptor>
    <!-- Typical standard value -->
    <lateAcceptanceSize>400</lateAcceptanceSize>
  </acceptor>
  <forager>
    <!-- Typical value -->
    <acceptedCountLimit>4</acceptedCountLimit>
  </forager>
</localSearch>
```

Local Search results



Cost ($) reduction

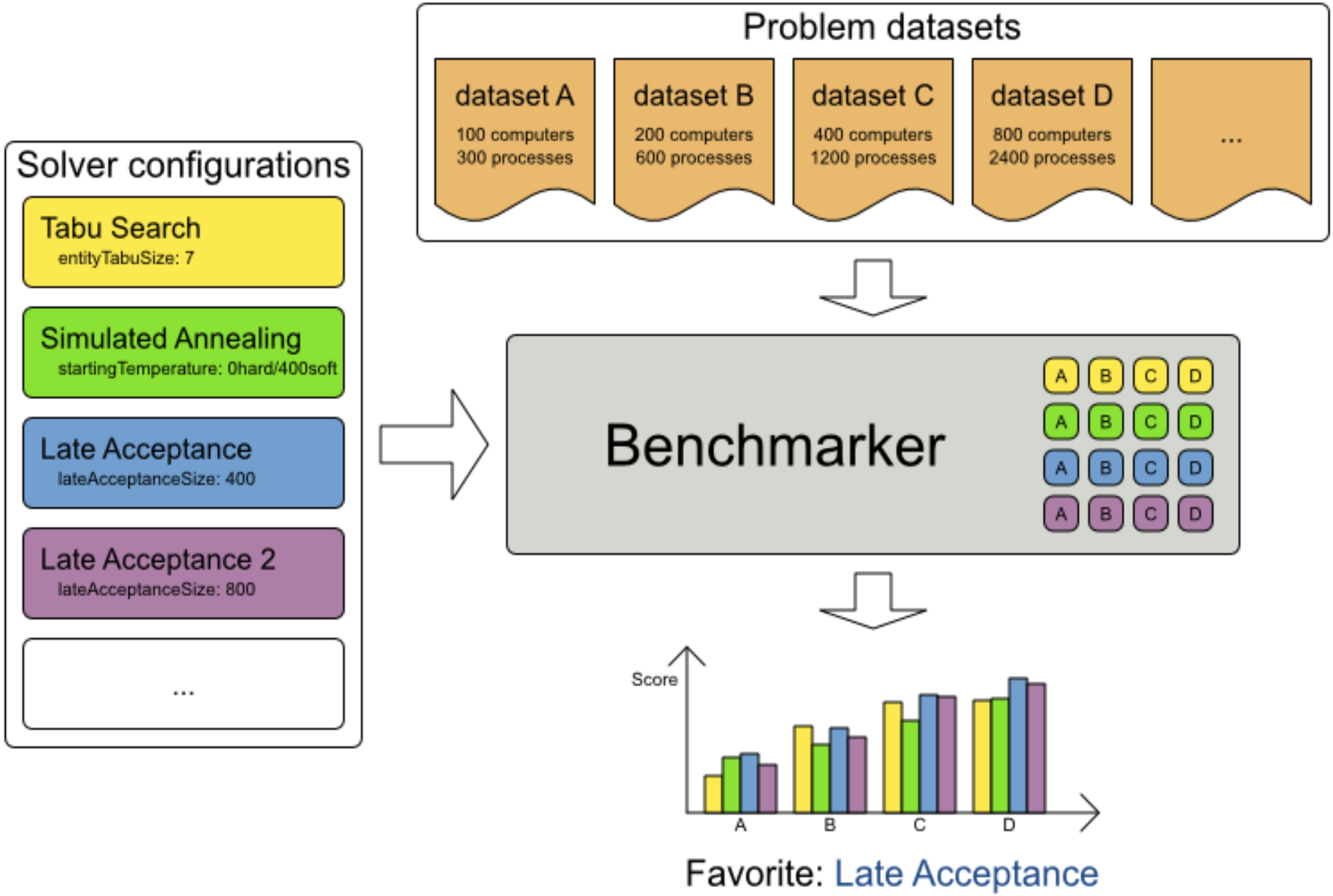


Optimization algorithms

- Exhaustive Search
  - Brute Force
  - Branch And Bound
- Construction Heuristics
  - First Fit (Decreasing)
  - Weakest/Strongest Fit (Decreasing)
  - Cheapest Insertion
- Metaheuristics (Local Search, ...)
  - Hill Climbing
  - Tabu Search
  - Strategic Oscillation Tabu Search
  - Simulated Annealing
  - Late Acceptance
  - Step Counting Hill Climbing

Benchmark overview

What optimization algorithm should we configure in production? The Benchmarker will tell us.



Favorite: Late Acceptance

Benchmark results

Demo

Gain by using OptaPlanner

Use case	Gain type	Avg	Min	Max
Cloud Balancing	Maintenance cost [1]	-18%	-16%	-21%
Machine Reassignment	Unbalanced load [2]	-63%	-25%	-97%
Vehicle Routing (Belgium datasets)	Distance [1]	-20%	-7%	-27%
Nurse rostering	Unhappiness [1]	-34%	-20%	-83%
Course scheduling	Unhappiness [1]	-66%	-26%	-100%

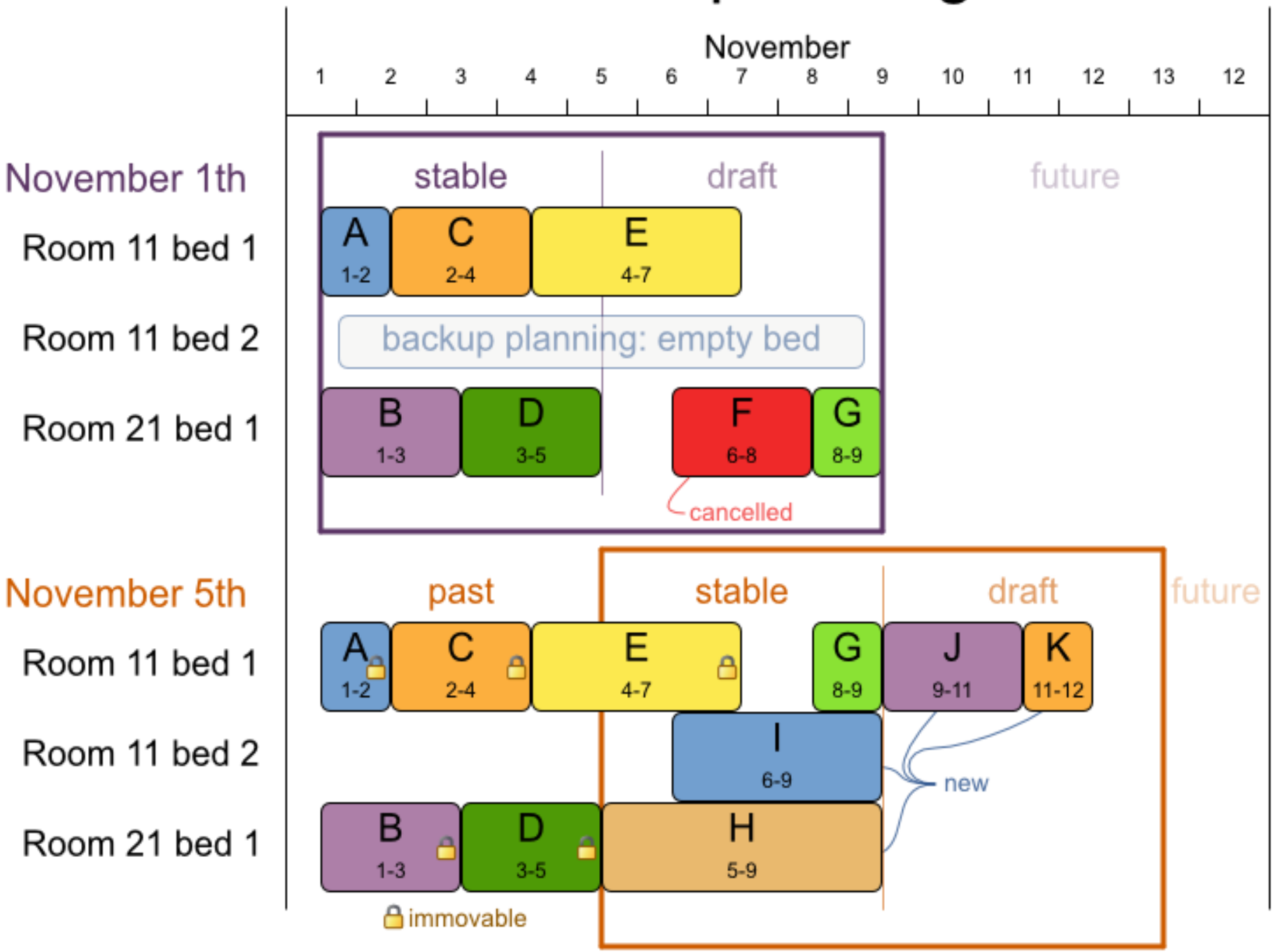
OptaPlanner in a 5 minute run

[1] Compared to traditional algorithms with domain knowledge.

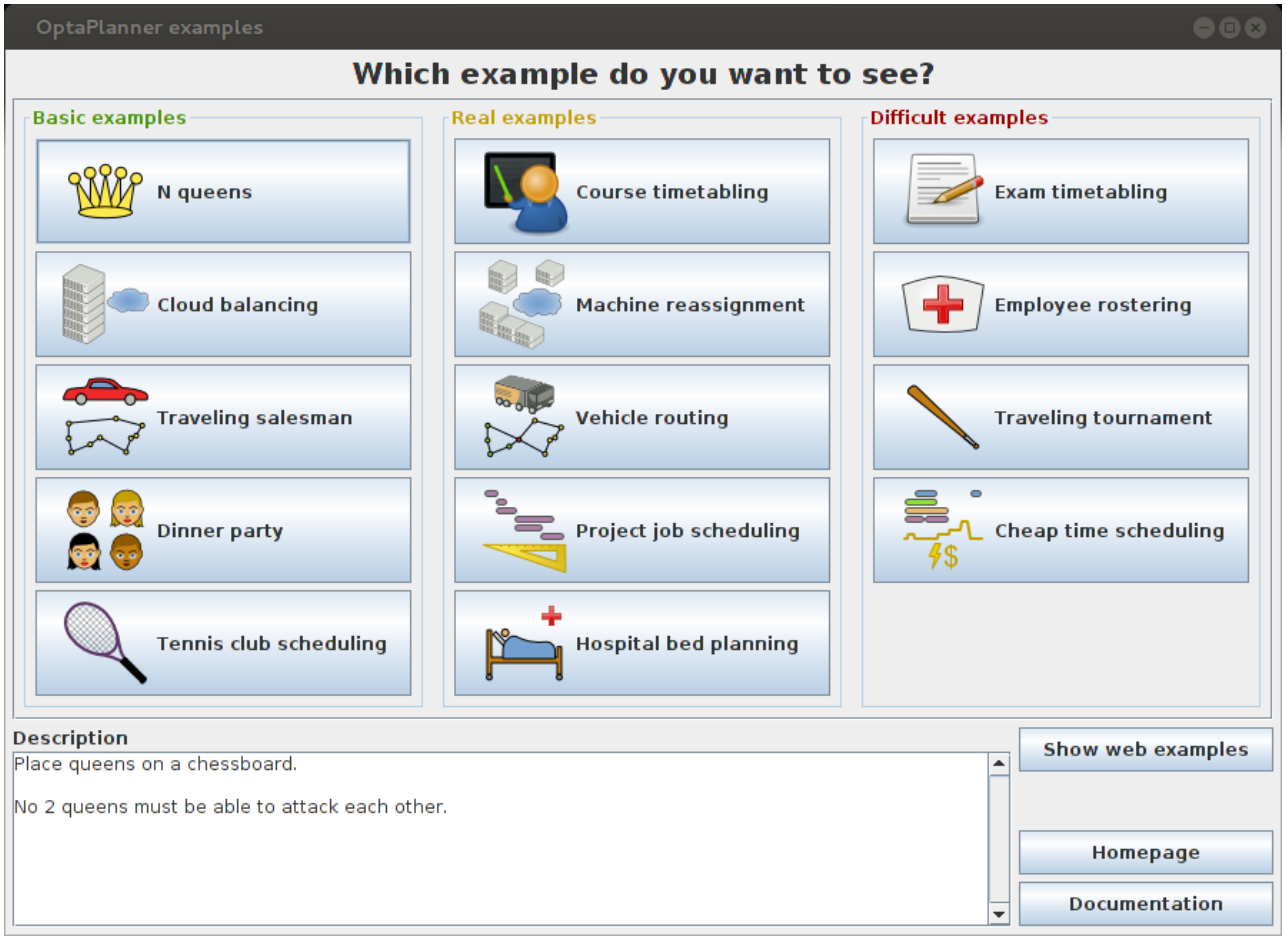
[2] Compared to initial assignments.

Repeated planning: continuous/real-time

Continuous planning



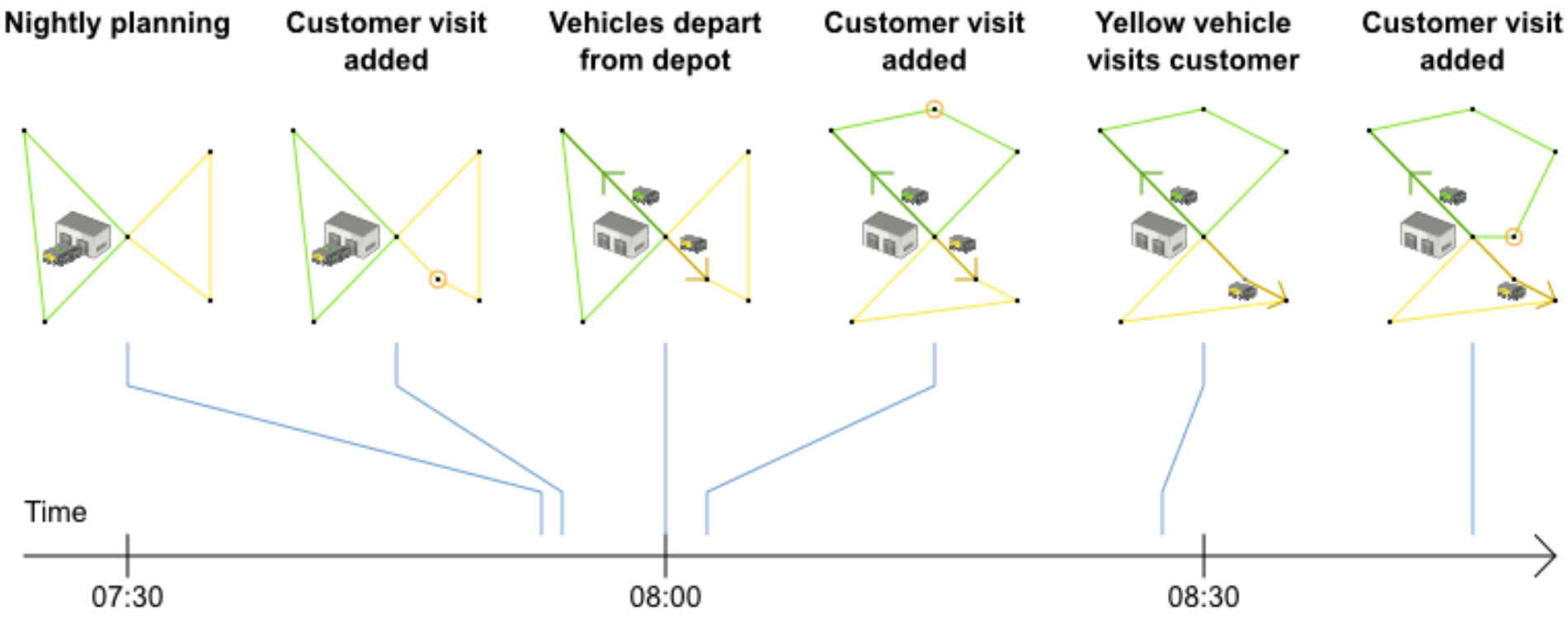
Continuous planning demo



Nurse rostering demo

Real-time planning

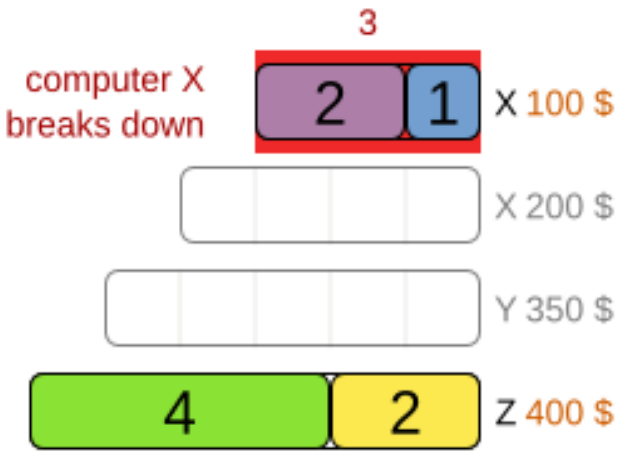
When the problem changes in real-time, the plan is adjusted in real-time.



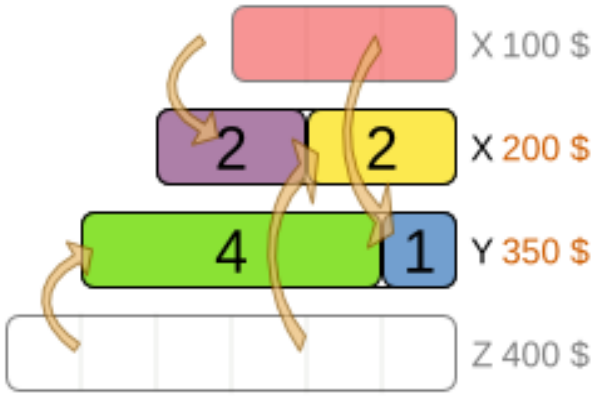
Nonvolatile replanning

Real-time planning must not distort the entire plan to deal with a real-time change.

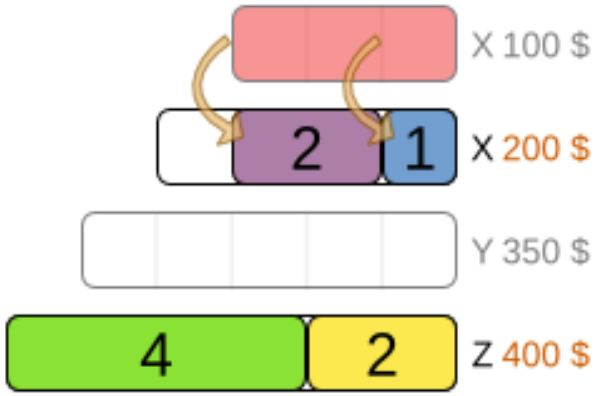
Original solution



Volatile solution



Nonvolatile solution



Normal score

-3hard / -500soft

0hard / -550soft

Highest score

0hard / -600soft

Adjusted score (-100 per moved process)

no moved processes: 0soft

-3hard / -500soft

4 moved processes: -400soft

0hard / -950soft

2 moved processes: -200soft

0hard / -800soft

Highest score

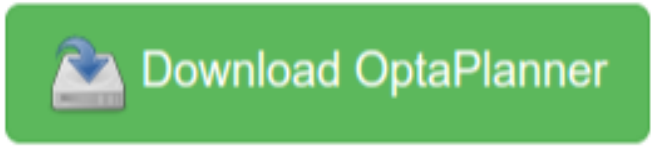
Summary

- OptaPlanner solves planning and scheduling problems
- Adding constraints: easy and scalable
- Switching/combining optimization algorithms: easy

Distribution zip

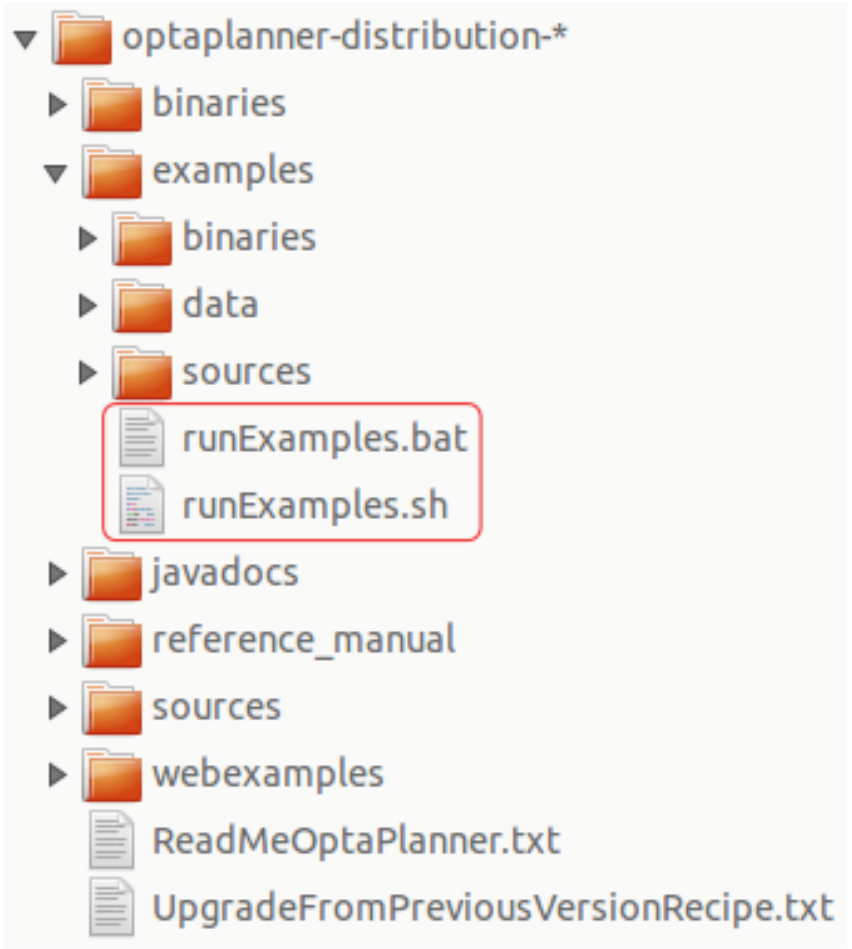
Running the examples locally

1. Surf to www.**optaplanner.org**

2. Click on 

3. Unzip optaplanner-distribution-*.zip

4. Open the directory `examples` and double click on `runExamples`



Build from source

- https://github.com/droolsjbpm/optaplanner (https://github.com/droolsjbpm/optaplanner)

```
$ git clone git@github.com:droolsjbpm/optaplanner.git
...
$ cd optaplanner
$ mvn clean install -DskipTests
...
$ cd optaplanner-examples
$ mvn exec:java
...
```

Q & A

- OptaPlanner homepage
  - http://www.optaplanner.org (http://www.optaplanner.org)
- Reference manual
  - http://www.optaplanner.org/learn/documentation.html (http://www.optaplanner.org/learn/documentation.html)
- Download/fork this presentation
  - http://www.optaplanner.org/learn/slides.html (http://www.optaplanner.org/learn/slides.html)

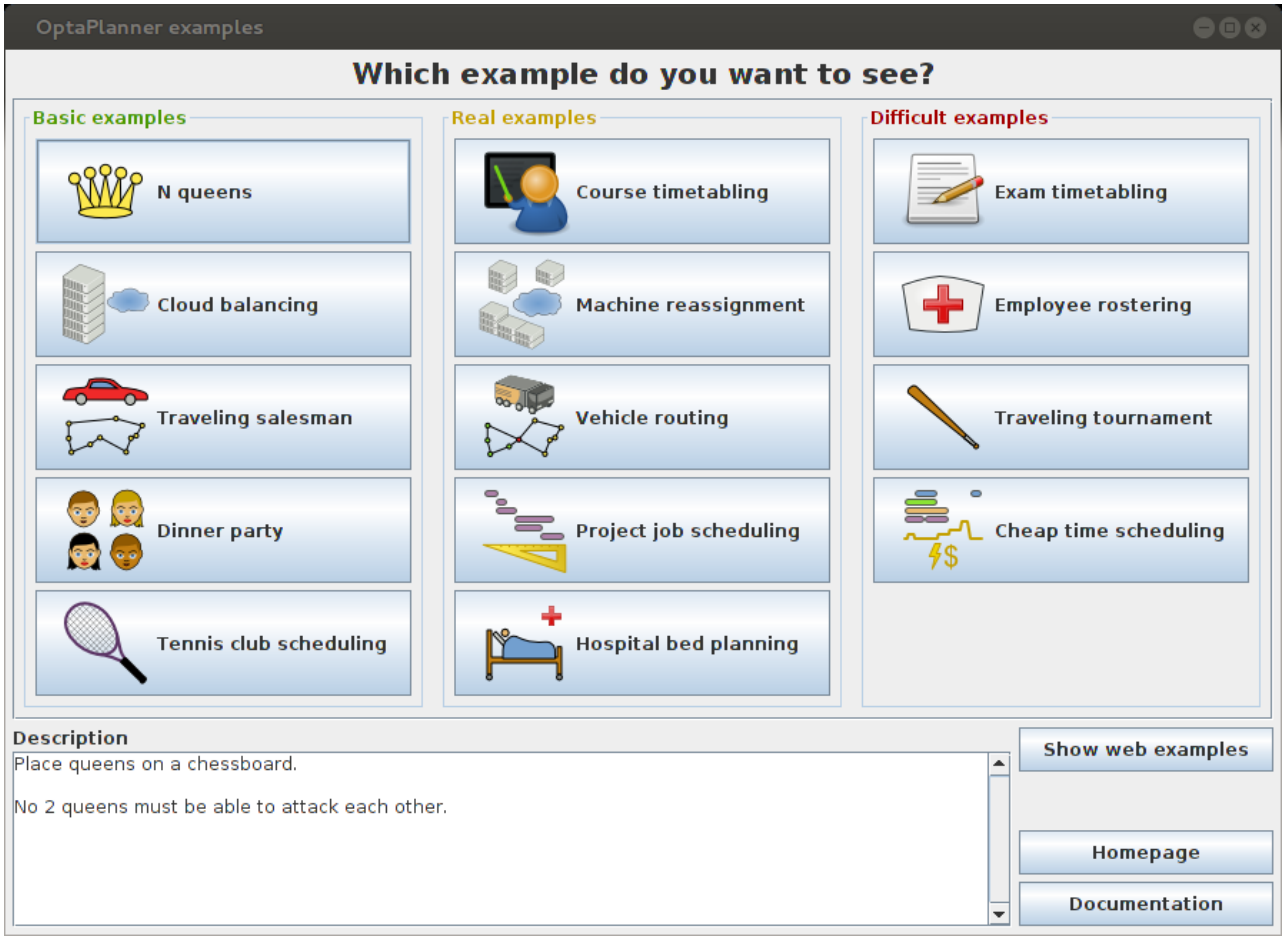
- What did you think of this presentation?
  - Twitter: @GeoffreyDeSmet (https://twitter.com/GeoffreyDeSmet)
  - Google+: +GeoffreyDeSmet (https://plus.google.com/+GeoffreyDeSmet)

Introduction to heuristics and metaheuristics for business resource optimization

by Geoffrey De Smet

OptaPlanner lead

N Queens demo

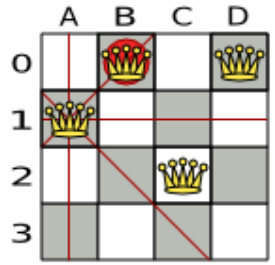


demo

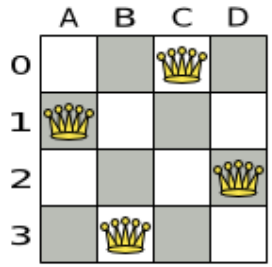
Simplified problem

N Queens

- Place n queens on a n sizes chessboard
- No 2 queens can attach each other



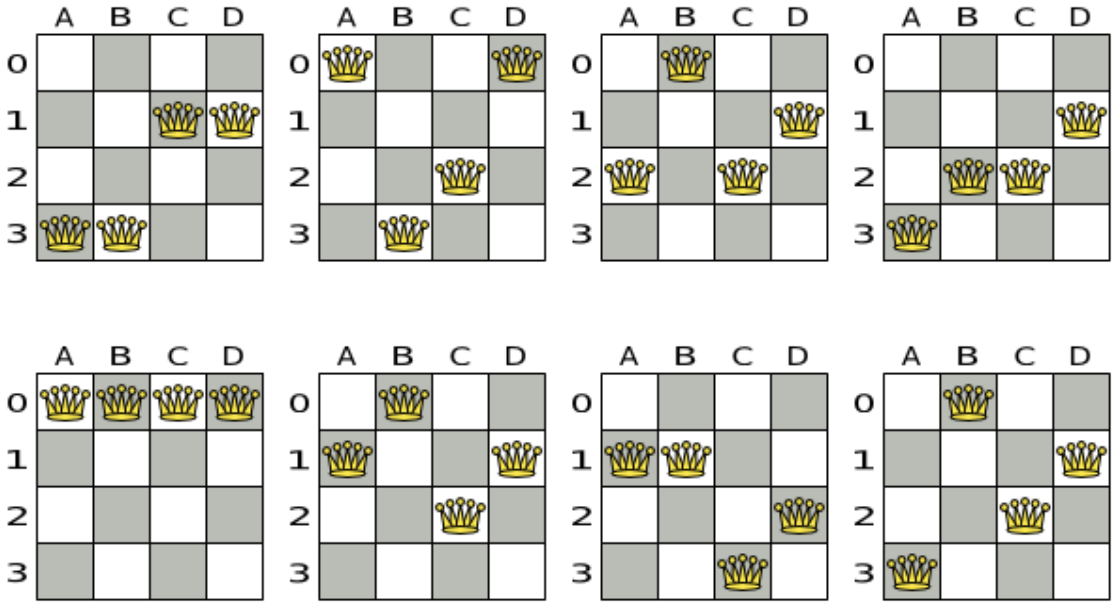
Bad



Good

- Imperfect example
  - Not NP-complete (shortcuts exist)

What solution is better?



- Need for **objective scoring**
- Better score ⇔ better solution
- Highest score ⇔ optimal solution

Positive and negative constraints

Pick the solution which maximizes apples and minimizes fuel usage

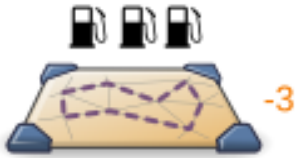
Maximize 🍏 ⇒ 🍏 = 1

<

<

Optimal solution

Minimize ⛽ ⇒ ⛽ = -1



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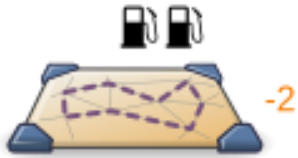
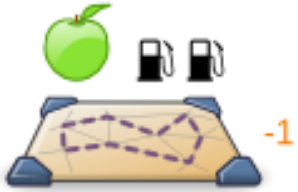


<

Optimal solution

Maximize 🍏 and minimize ⛽ ⇒ 🍏 = 1 & ⛽ = -1



<

<

Optimal solution

Score weighting

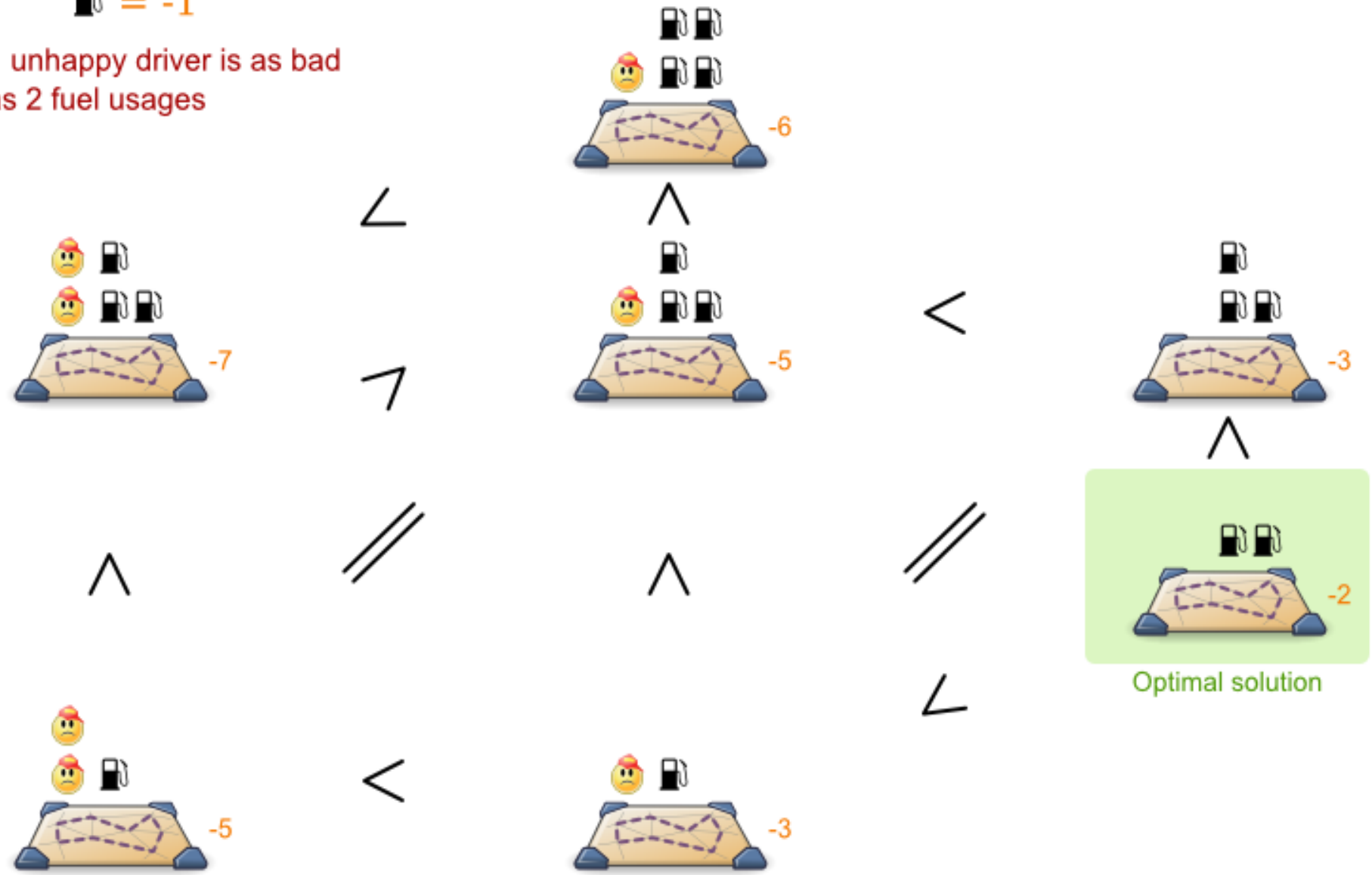
= 2

⇒ = -2

= -1

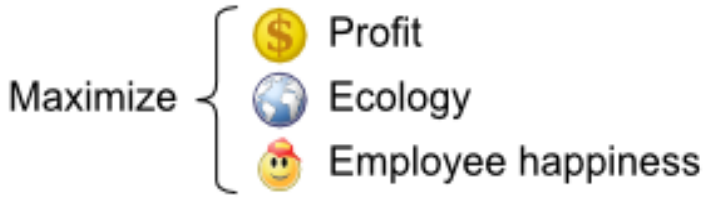
1 unhappy driver is as bad as 2 fuel usages

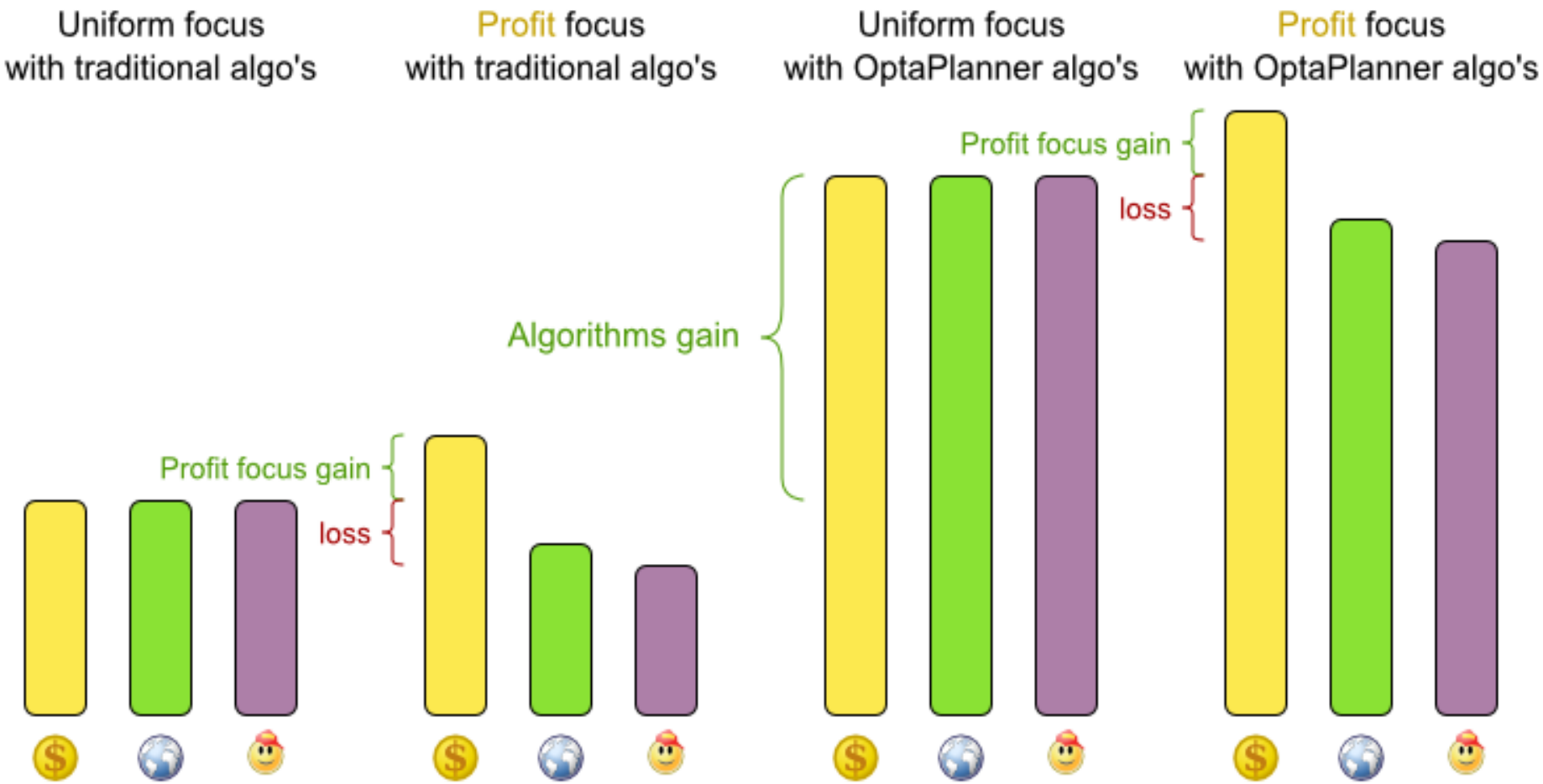
Minimize driver unhappiness
Minimize fuel usage



Score tradeoff in perspective

Picking the right tradeoff is less important than using better algorithms.



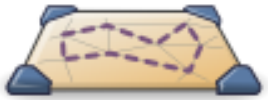


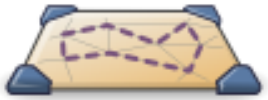
Score weight type

⛽ = 0.01 $

Use the correct number type

	Fuel usage	double double-precision 64-bit IEEE 754 floating point	BigDecimal arbitrary-precision signed decimal number
Vehicle X	⛽⛽⛽	0.03	0.03
Vehicle Y	⛽⛽⛽	0.03	0.03
Total		0.06	0.06 Highest score
Vehicle X	⛽	0.01	0.01
Vehicle Y	⛽⛽⛽⛽⛽	0.05	0.05
Total		0.060000000000000005 Highest score	0.06 Highest score



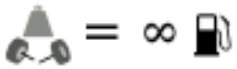


SimpleDoubleScore
score : double

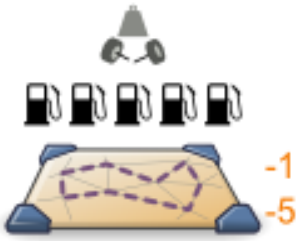
SimpleBigDecimalScore
score : BigDecimal

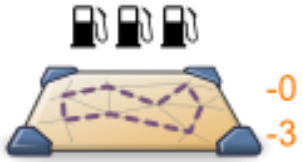
Score levels

First minimize overloaded truck axles,
then minimize fuel usage

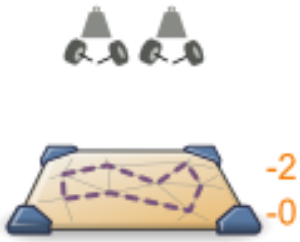


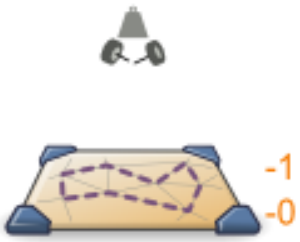
1 overloaded axle is worse
than any number of fuel usages





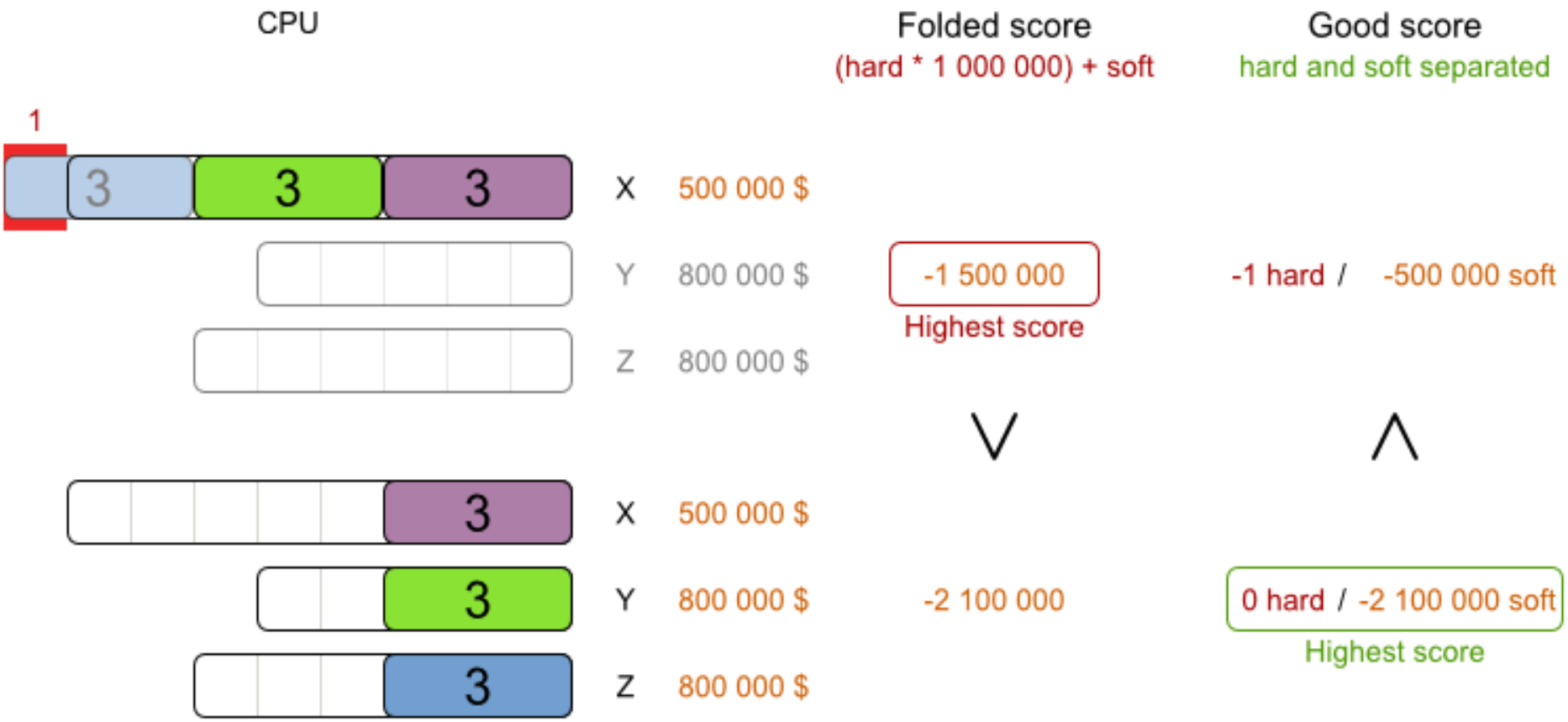
Optimal solution



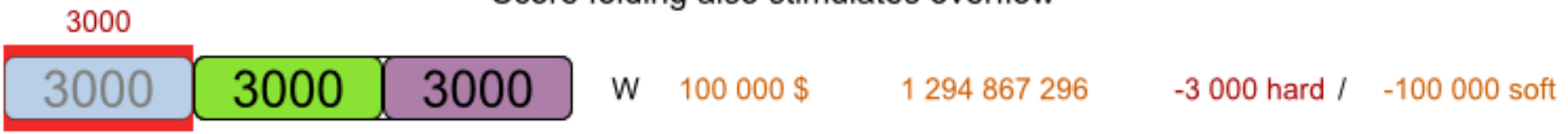


Score folding is broken

Don't mix score levels

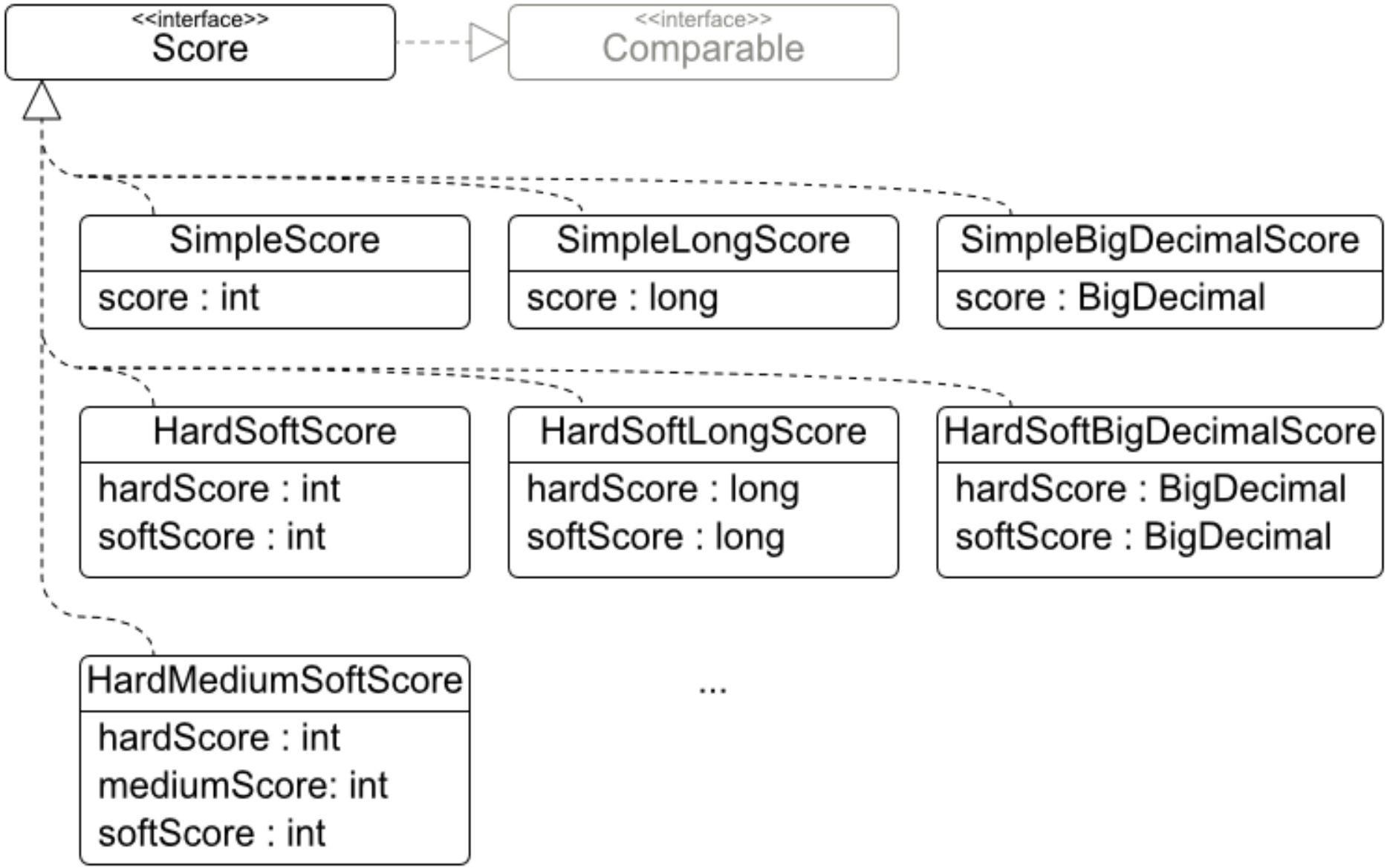


Score folding also stimulates overflow



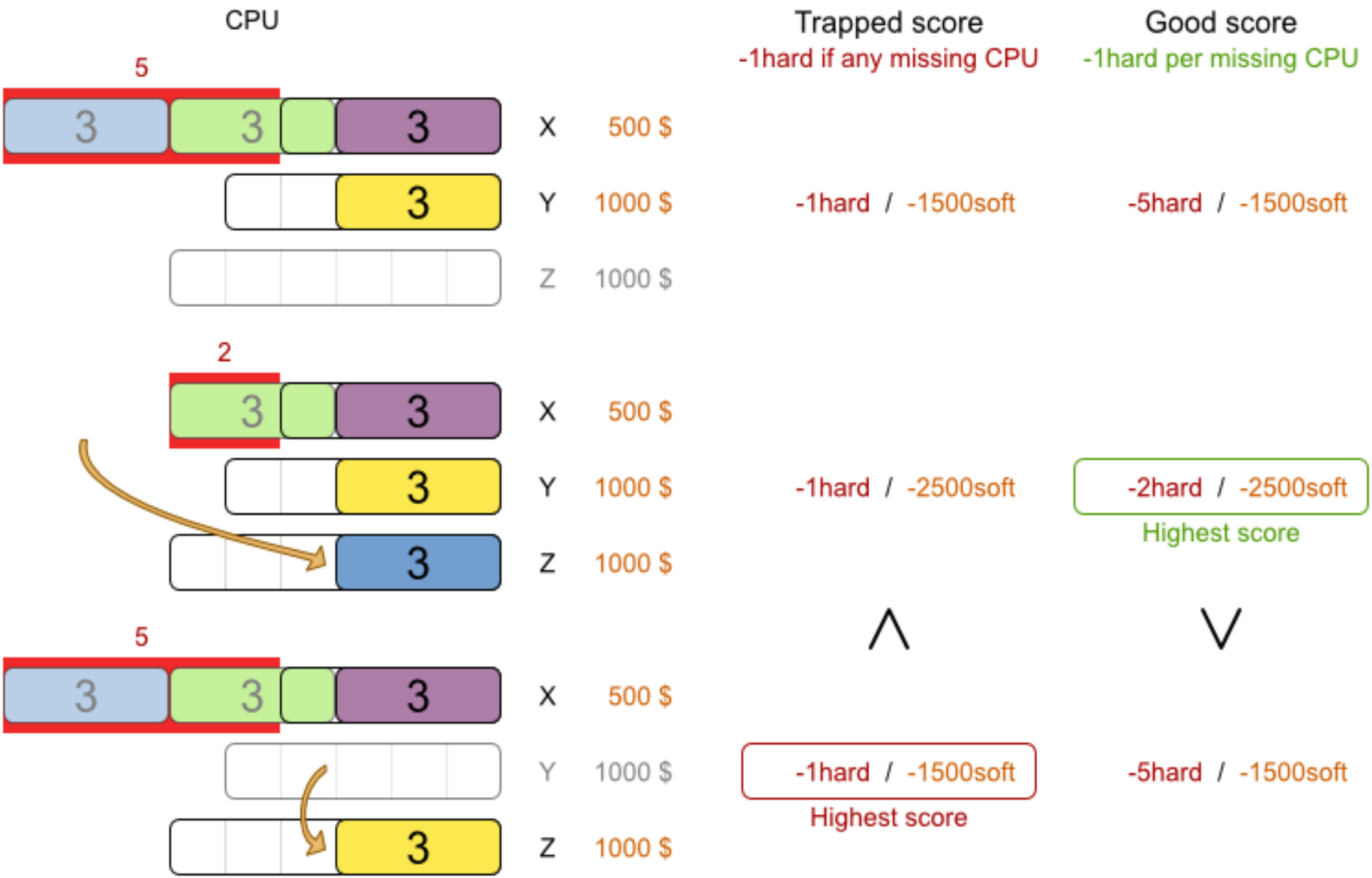
Score class diagram

Choose a Score implementation or write a custom one



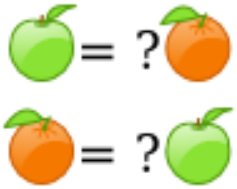
Score trap

There are degrees of infeasibility



Pareto optimization scoring

Maximize apples and oranges harvest
Don't compare apples and oranges



1 apple is worth an unknown number of oranges
1 orange is worth an unknown number of apples

Optimal solution A

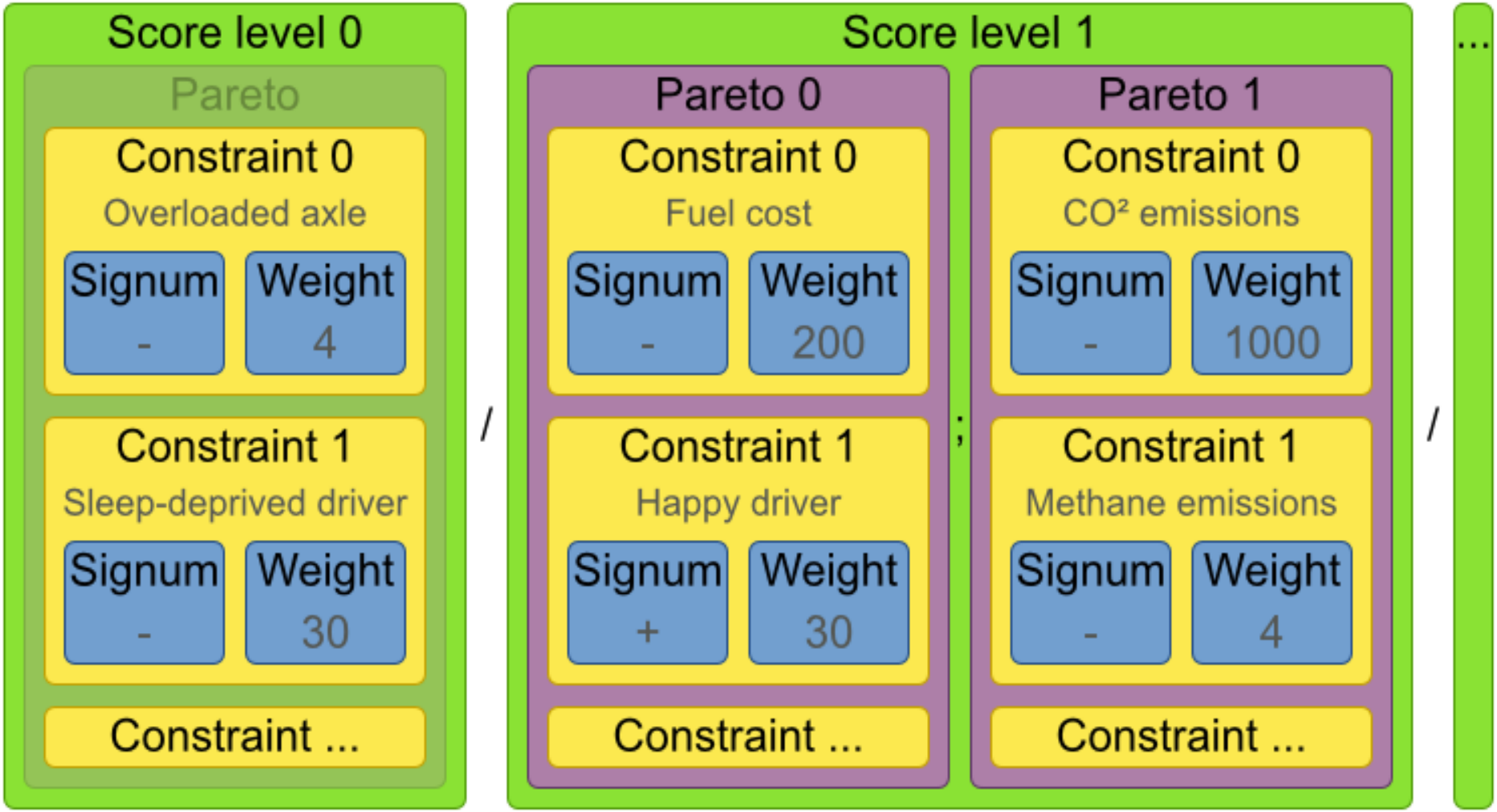
Optimal solution B

Pareto optimal

Only pareto optimal solutions
are shown to the user
User decides between A and B

Score composition

How are the score techniques combined?

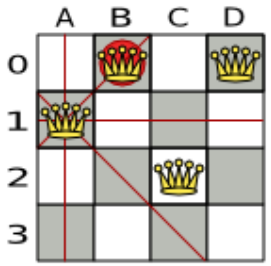


-34 / -170 ; -1004 / ...

Score for 1 solution

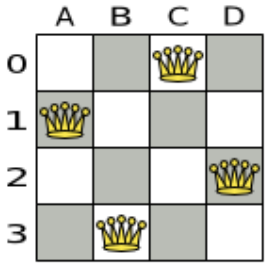
N Queens

- Hard constraints:
  - -1 for every pair of conflicting queens
- Soft constraints:
  - None



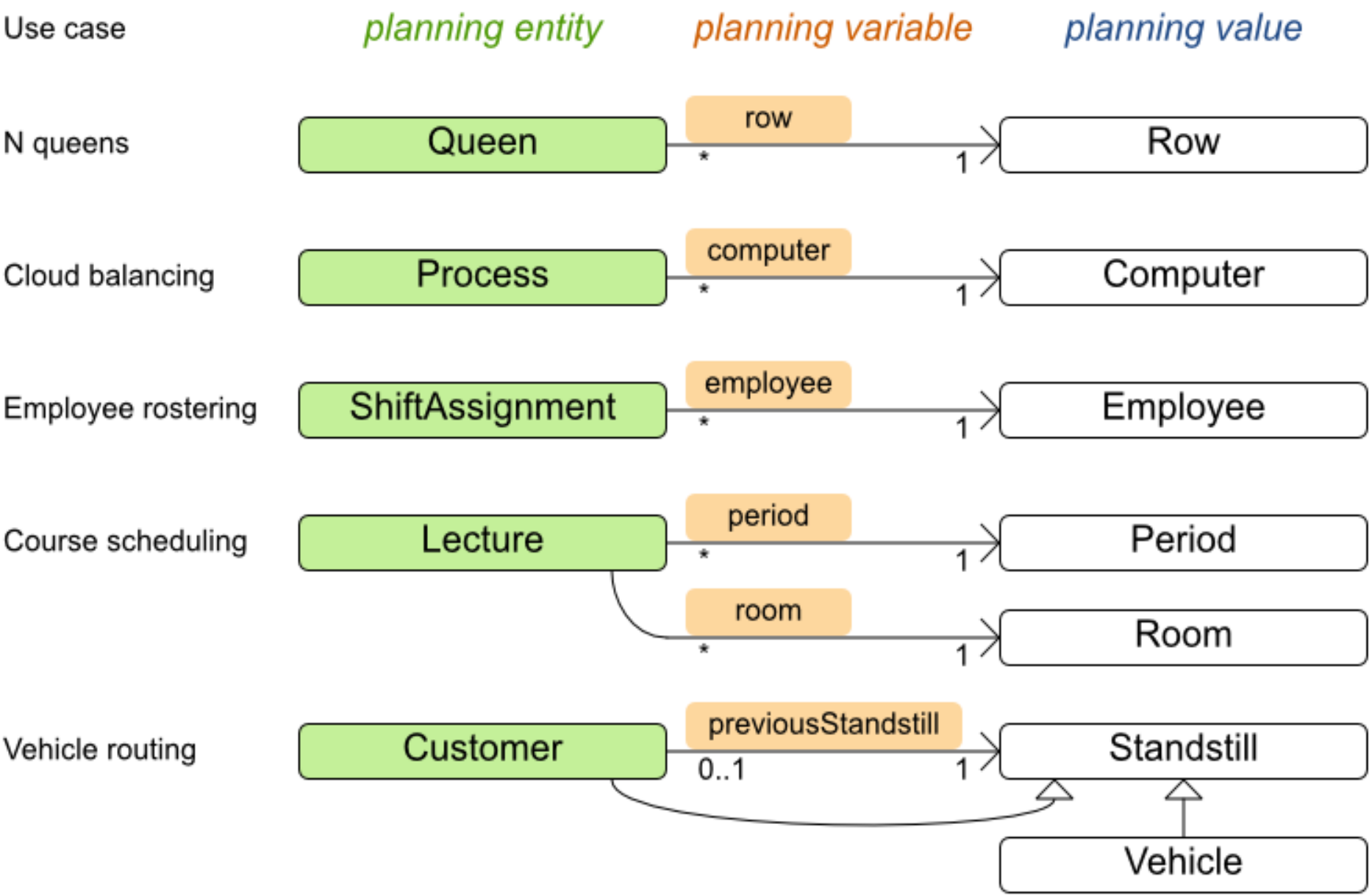
Score = -2

Conflicts: A-B, B-D

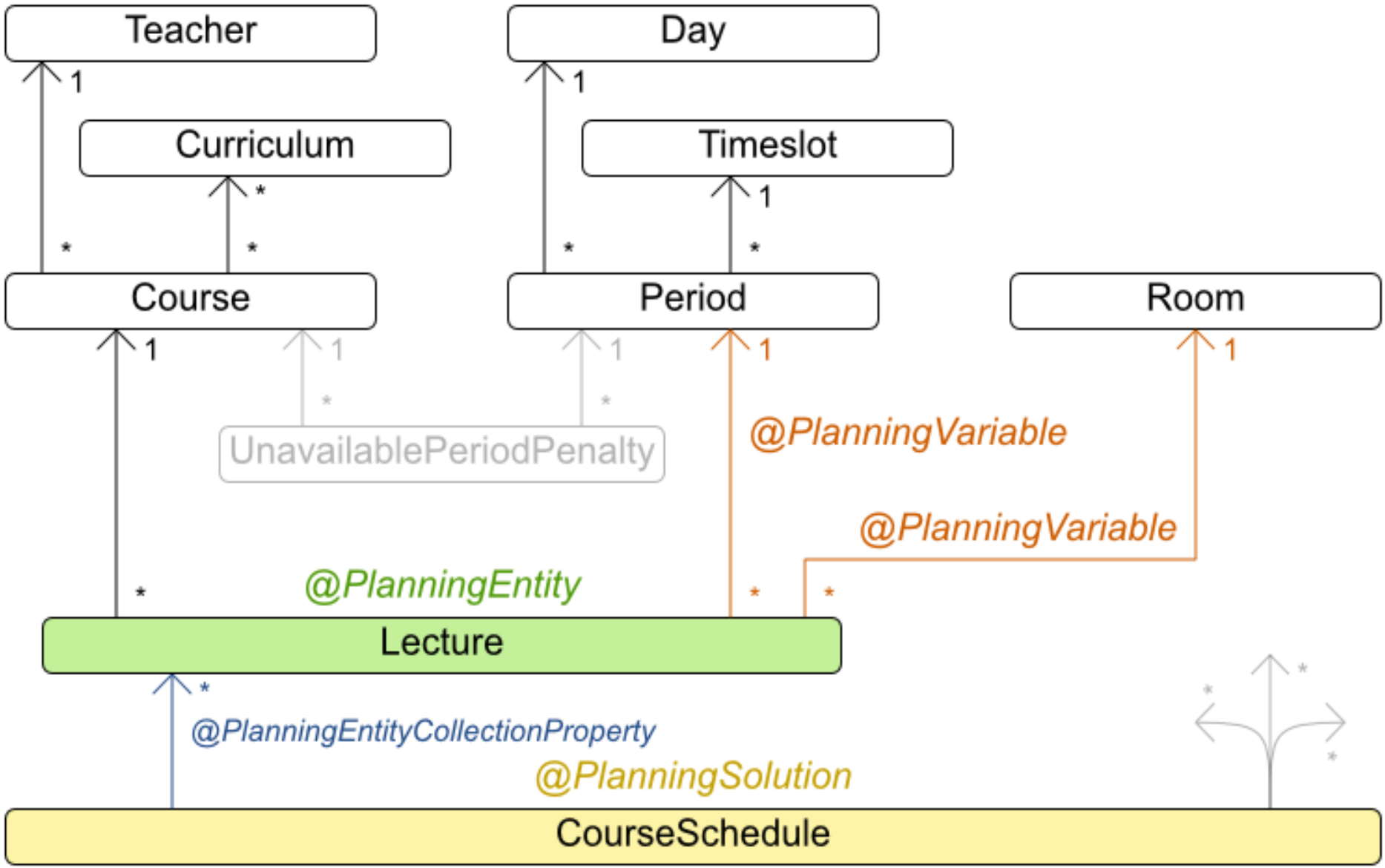


Score = 0

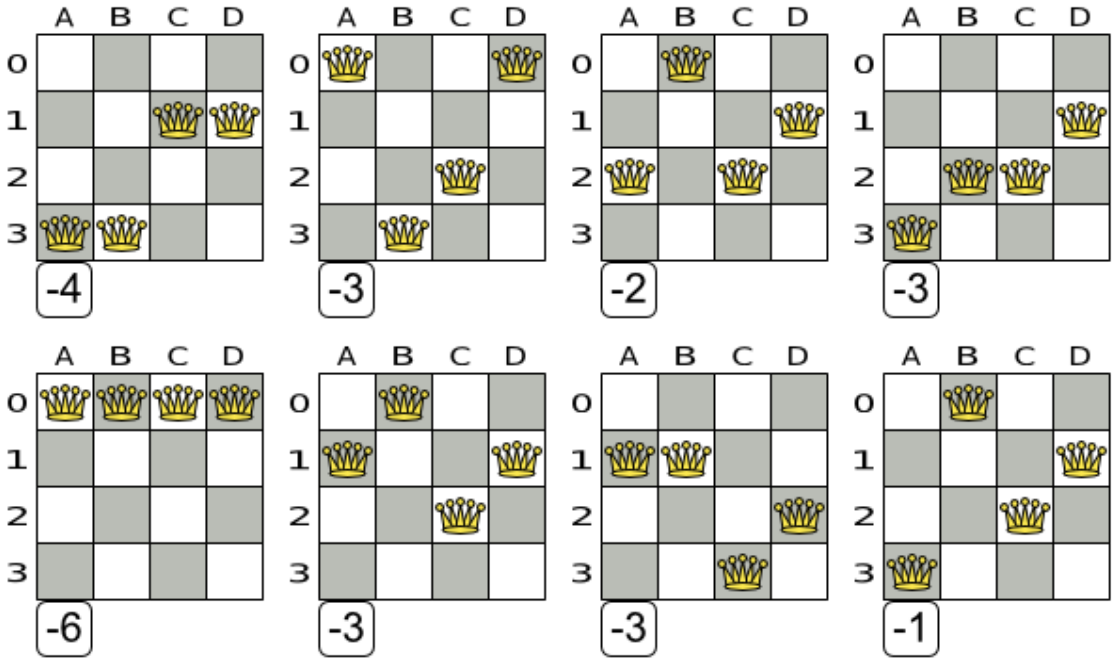
Entity, variable and value examples



Curriculum course class diagram

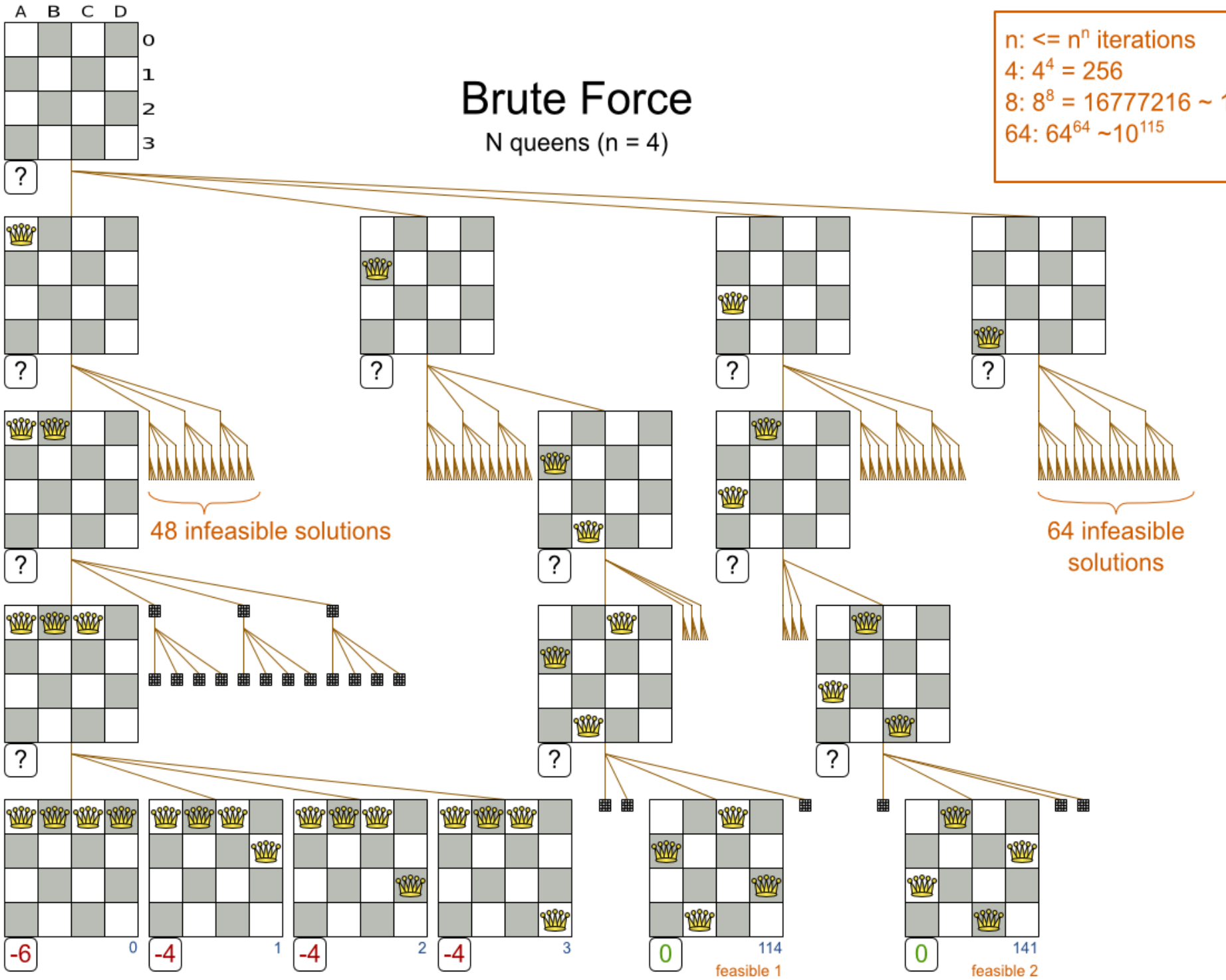


How do we find the best solution?

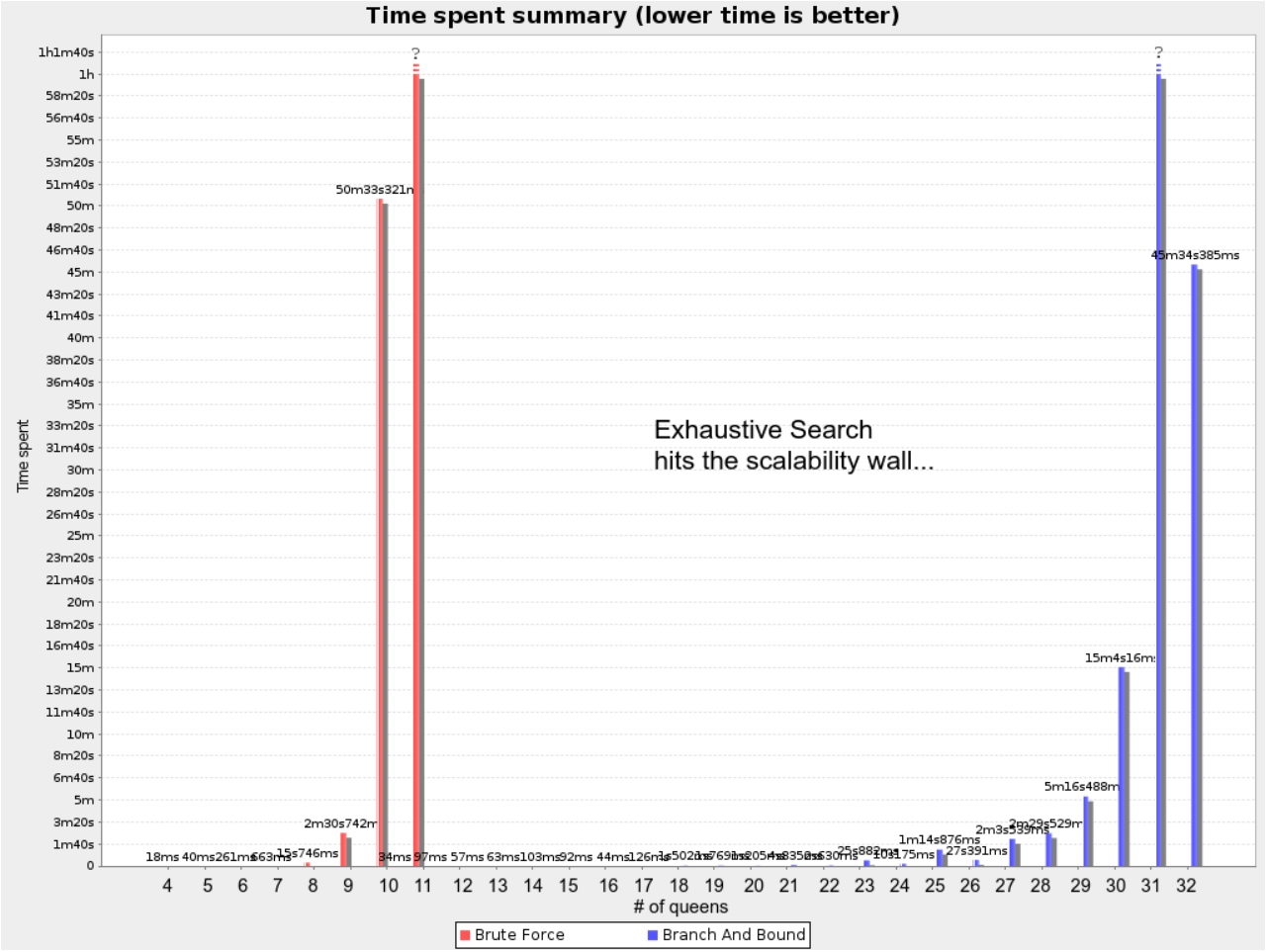


- Need for **optimization algorithms**
- Best solution in available time

Brute Force


A B C D
0
1
2
3
?
Brute Force
N queens (n = 4)
n: <= n^n iterations
4: 4^4 = 256
8: 8^8 = 16777216 ~ 10^7
64: 64^64 ~10^115
48 infeasible solutions
64 infeasible solutions
-6
0
-4
1
-4
2
-4
3
0
114
feasible 1
0
141
feasible 2

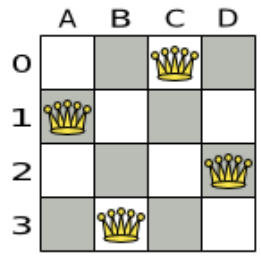
Brute Force scalability



8 queens = 15.7 seconds
9 queens = 2.5 minutes (times 10)
10 queens = 0.83 hours (times 20)

How many combinations for 100 queens?

- 1 queen per column
- 100 queens ⇒ 100 variables
- 100 rows ⇒ 100 values per variable



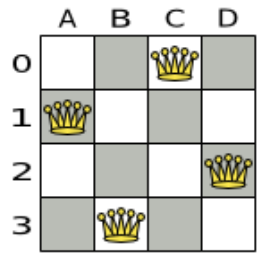
Source: NASA (wikipedia)

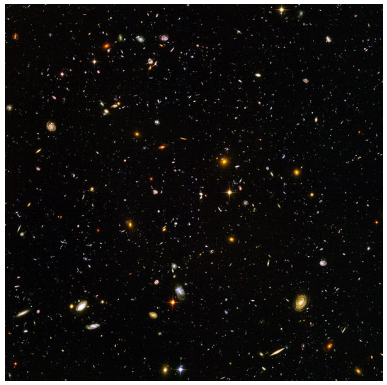
> humans?

7 000 000 000

How many combinations for 100 queens?

- 1 queen per column
- 100 queens ⇒ 100 variables
- 100 rows ⇒ 100 values per variable



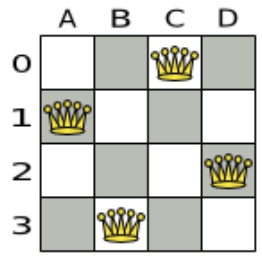


Source: NASA and ESA (wikipedia)

> minimum atoms
in the observable universe?
10^{80}

How many combinations for 100 queens?

- 1 queen per column
- 100 queens ⇒ 100 variables
- 100 rows ⇒ 100 values per variable

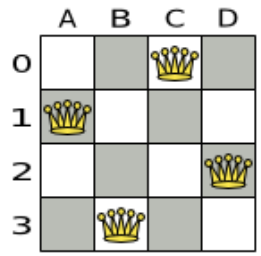


$$100^{100} = 10^{200}$$

```
1 0000000000 0000000000 0000000000 0000000000 0000000000
  0000000000 0000000000 0000000000 0000000000 0000000000
  0000000000 0000000000 0000000000 0000000000 0000000000
  0000000000 0000000000 0000000000 0000000000 0000000000
```

How many combinations for n queens?

- 1 queen per column
- n queens ⇒ n variables
- n rows ⇒ n values per variable



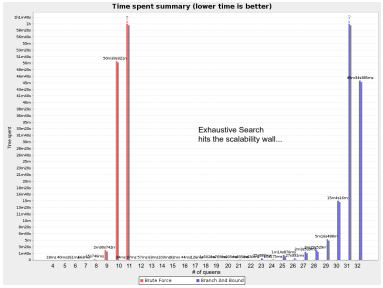
$$n^n$$

$$|valueSet|^{|variableSet|}$$

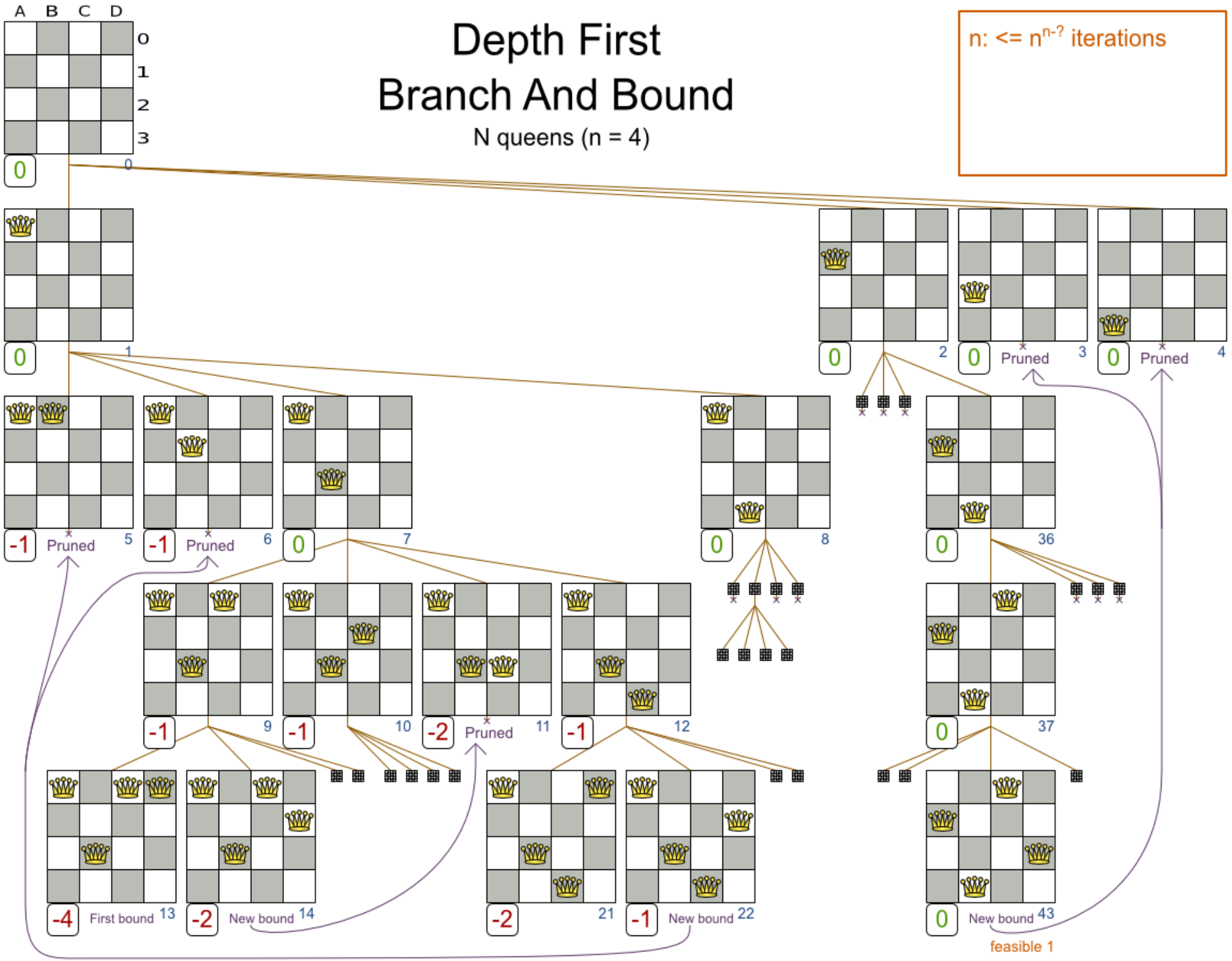
How long?

Presume 10^9 scores/ms ⇒ 10^{20} scores/year

Queens	Combinations	Calculation time
100	$100^{100} = 10^{200}$	10^{180} years
1000	$1000^{1000} = 10^{3000}$	10^{2980} years
10000	$10000^{10000} = 10^{40000}$	10^{39980} years



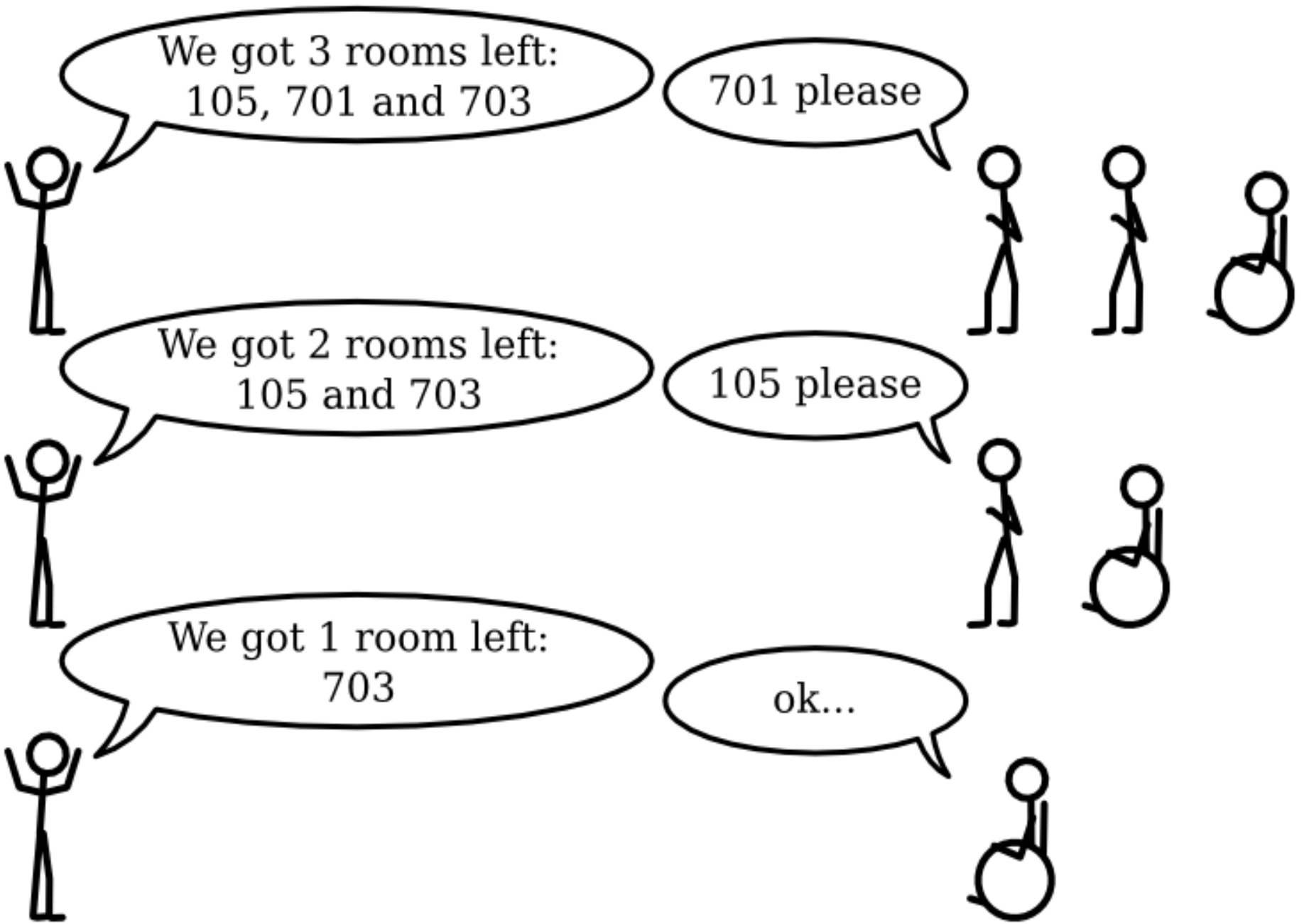
Moore's law == a drop in the ocean


Depth First
Branch And Bound
N queens (n = 4)
n: <= n^n-? iterations
A B C D
0
1
2
3
Pruned
First bound
New bound
feasible 1

Exhaustive Search doesn't scale

- Branches explode exponentially
- Not enough CPU
- Not enough memory

First Fit

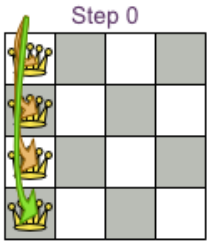

We got 3 rooms left:
105, 701 and 703
701 please
We got 2 rooms left:
105 and 703
105 please
We got 1 room left:
703
ok...

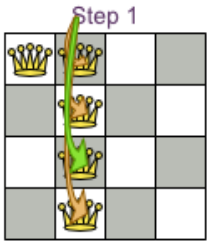
Construction Heuristic: First Fit

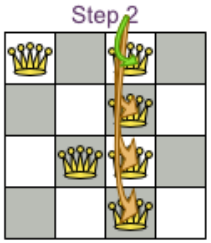
N queens (n = 4)

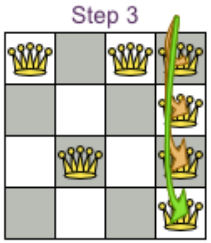
1 entity per step ordered arbitrary

n: <= n*n iterations
4: 4*4 = 16
8: 8*8 = 64
64: 64*64 = 4096

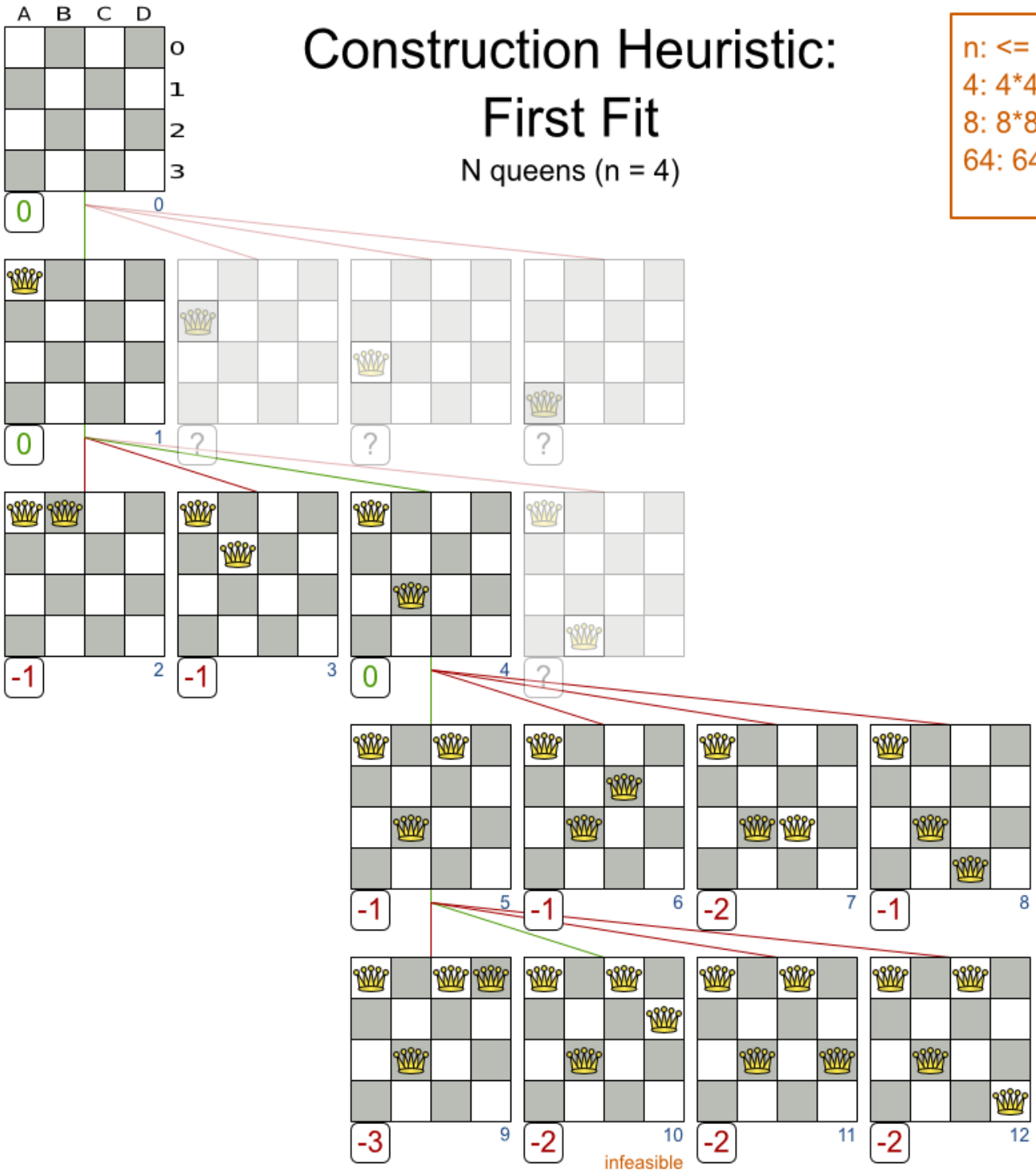




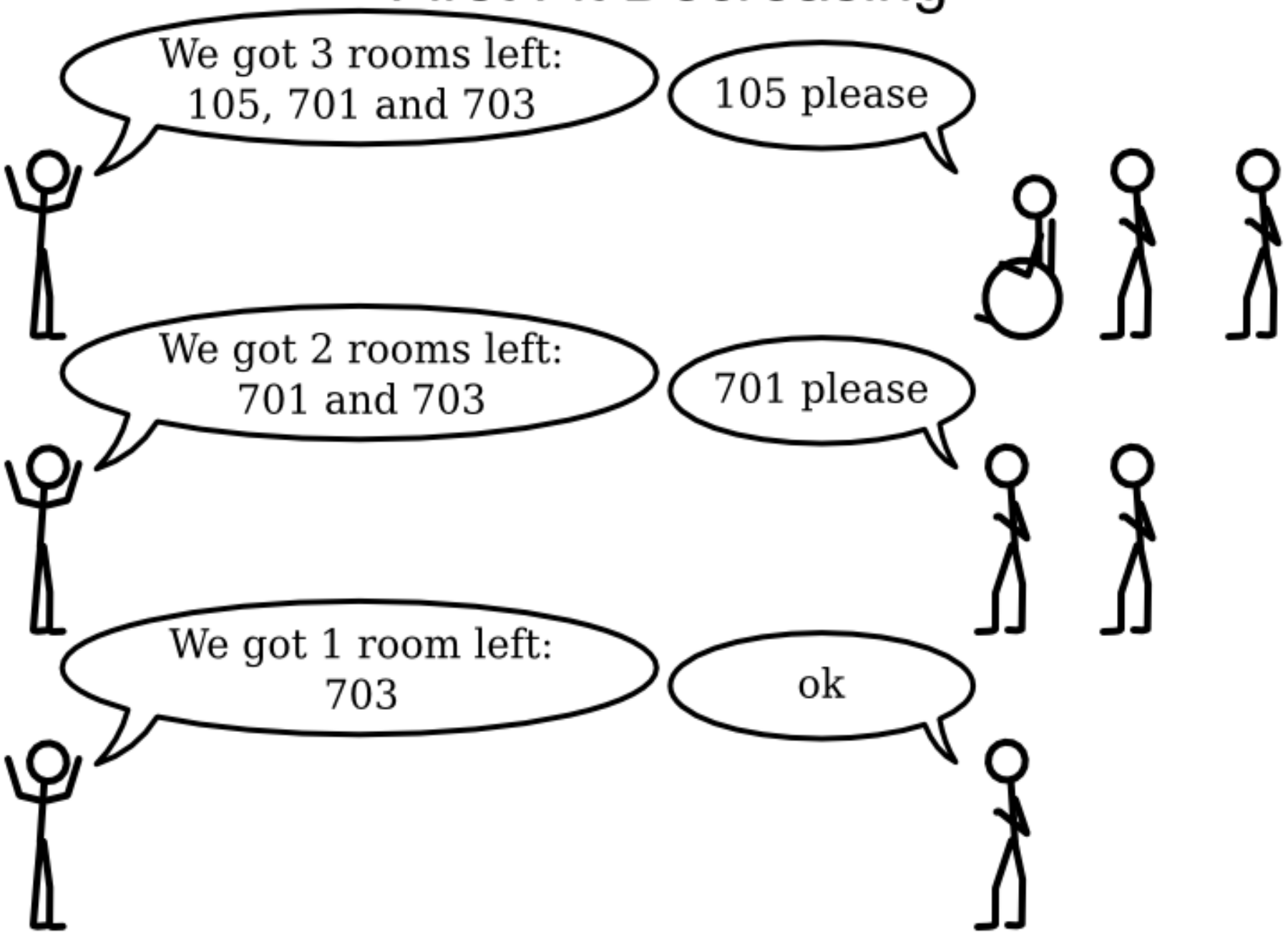




The end



First Fit Decreasing



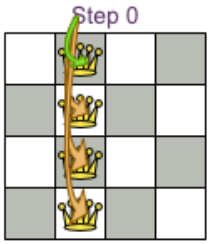
Construction Heuristic: First Fit Decreasing

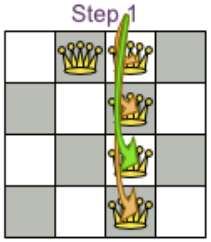
N queens (n = 4)

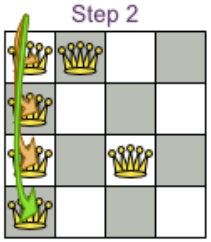
1 entity per step ordered in decreasing difficulty

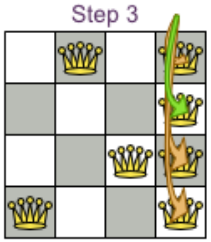
n: <= n*n iterations
4: 4*4 = 16
8: 8*8 = 64
64: 64*64 = 4096

Middle queens are more difficult to place, so we place them first

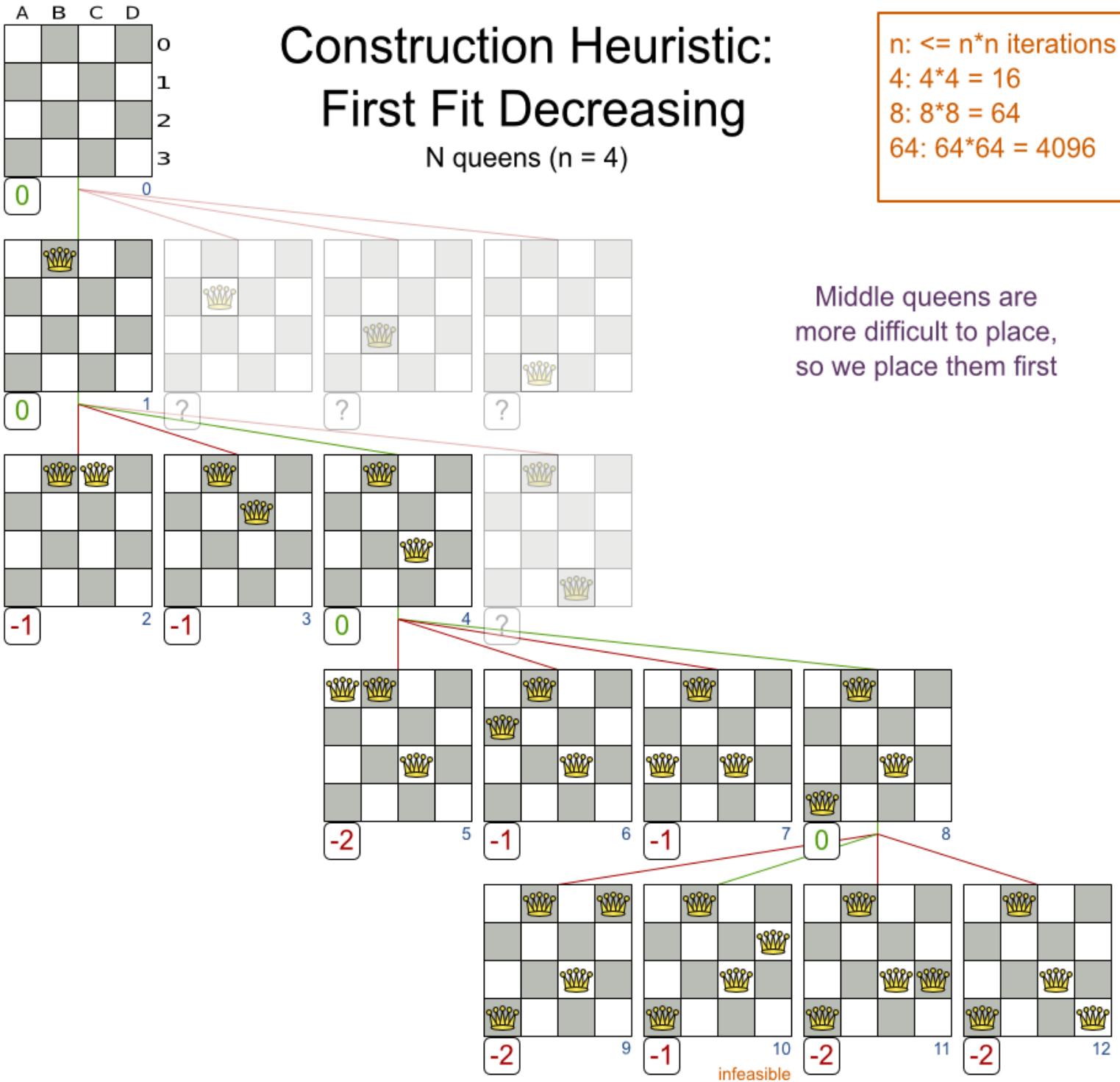




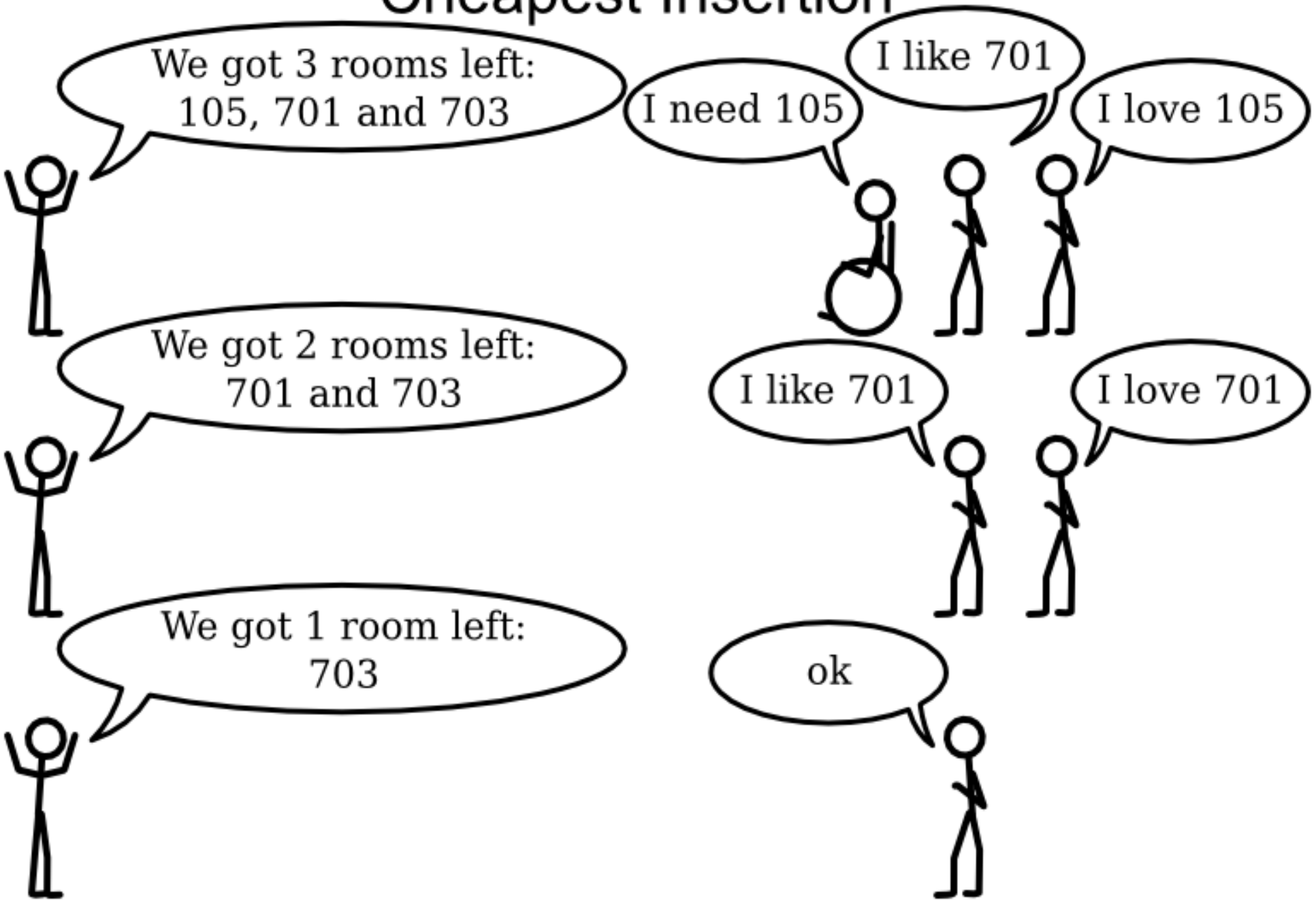




The end



Cheapest Insertion

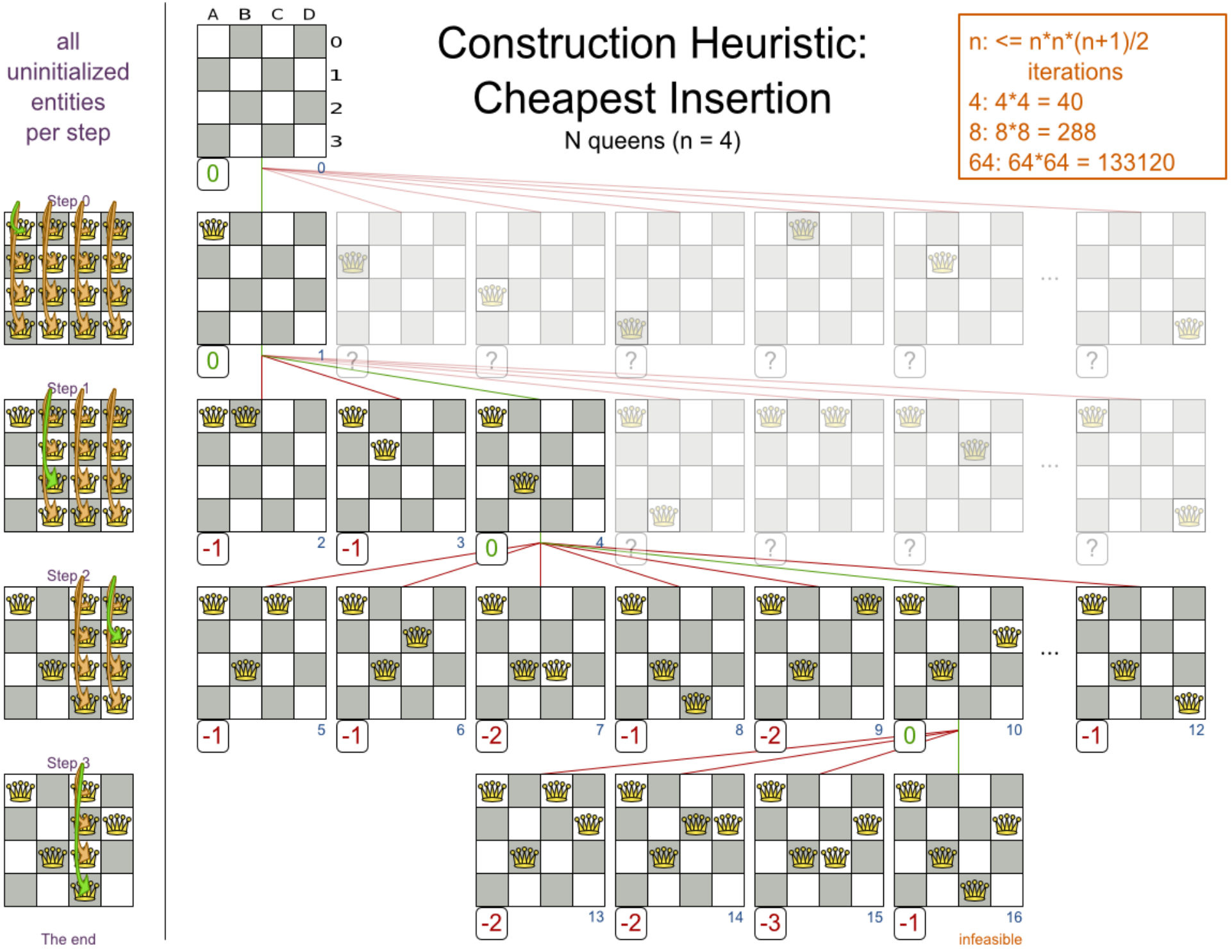


Construction Heuristic: Cheapest Insertion

N queens (n = 4)

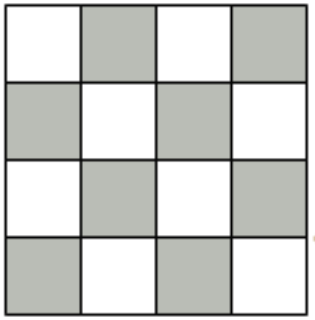
n: <= n*n*(n+1)/2 iterations
4: 4*4 = 40
8: 8*8 = 288
64: 64*64 = 133120

all uninitialized entities per step



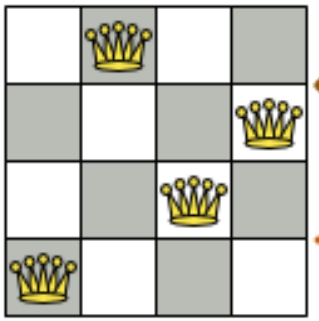
General phase sequence

First a construction heuristic,
then metaheuristics



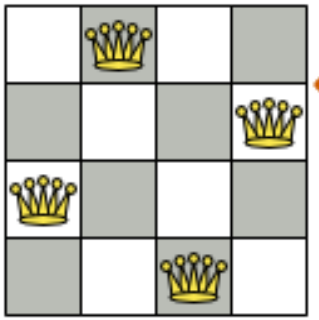
Construction heuristic

First Fit Decreasing



Metaheuristic

Tabu Search



Scope overview

Each scope triggers lifecycle events

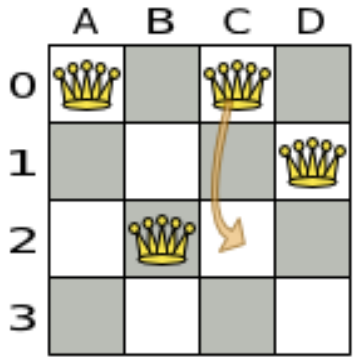
Move types

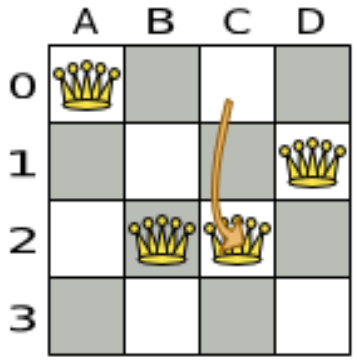
- Change move
- Swap move
- ...

ChangeMove

Change 1 variable of 1 entity

N queens

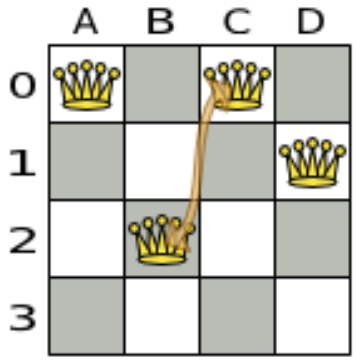


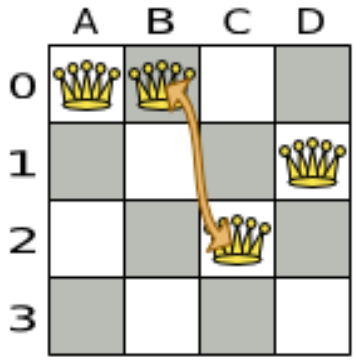


SwapMove

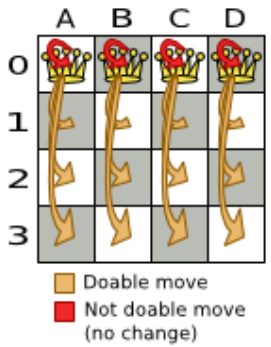
Swap all variables of 2 entities

N queens



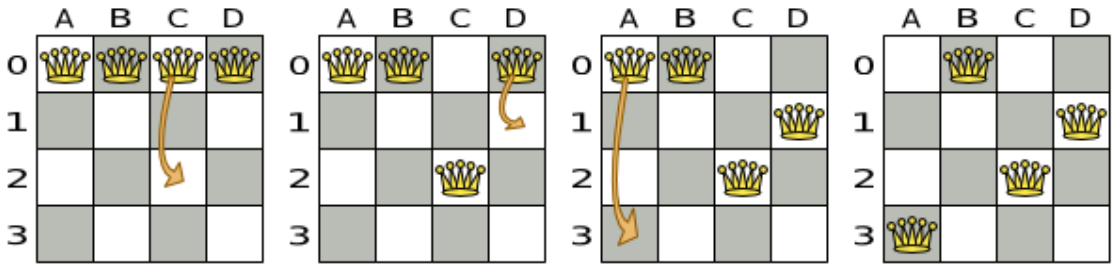


All change moves



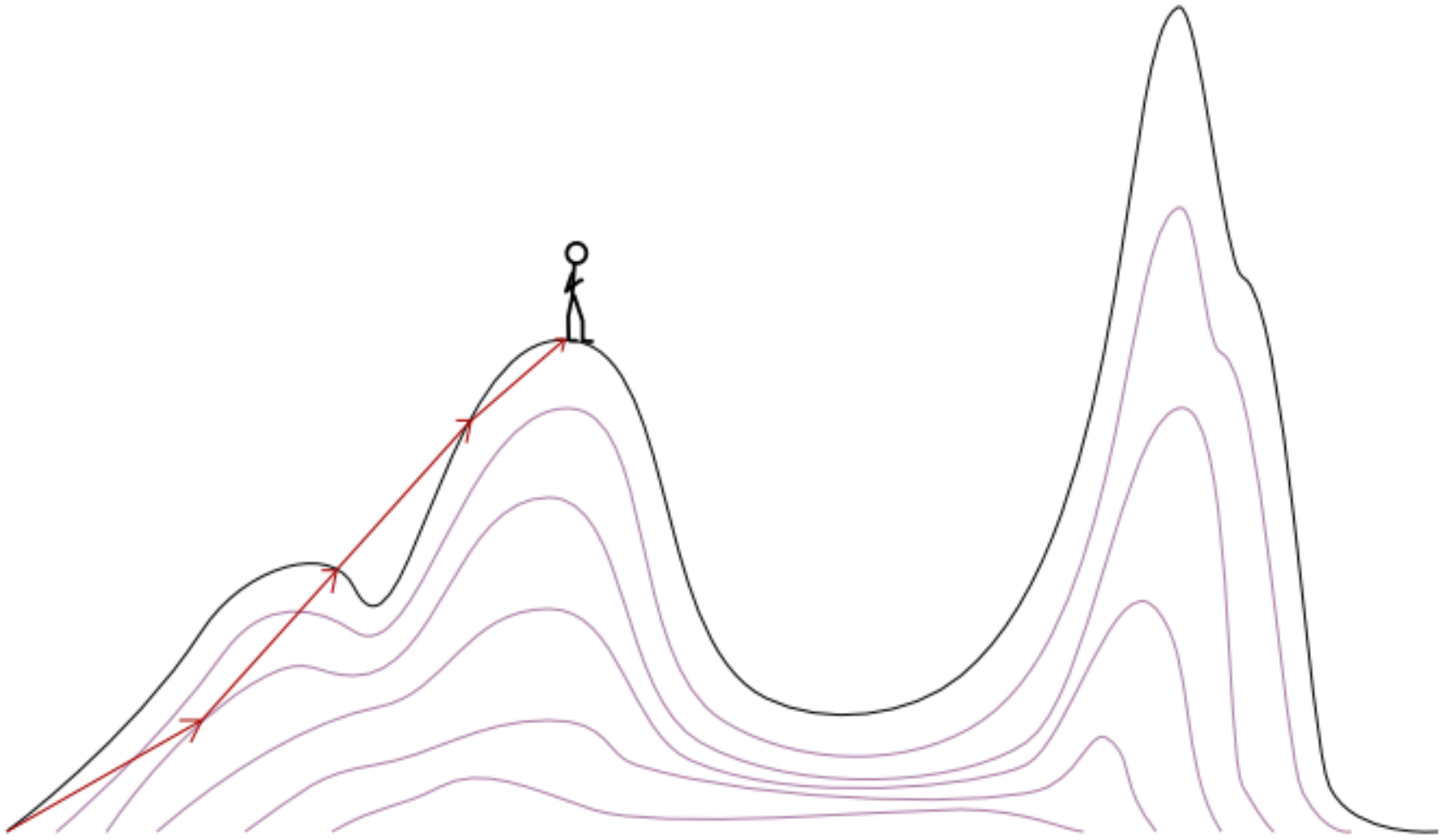
n	# moves	# solutions
4	16	256
8	64	16777216
64	4096	10^{116}
n	n^2	n^n

Multiple moves



Multiple moves can reach any solution

Hill climbing

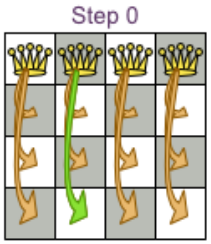


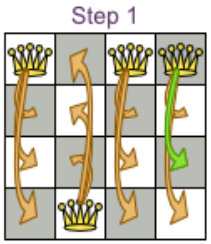
Local Search: Hill Climbing

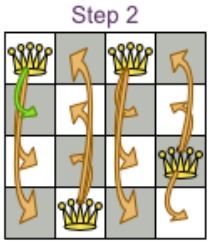
N queens (n = 4)

n: <= s * n^2 iterations

Selected moves for each step







Uses a search path, not a search tree

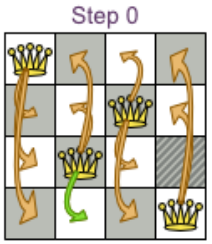
⇒ highly scalable

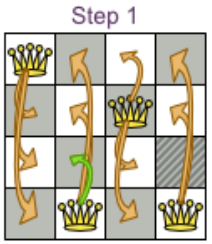
Hill Climbing gets stuck in local optima

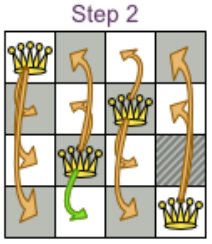
N queens (n = 4)

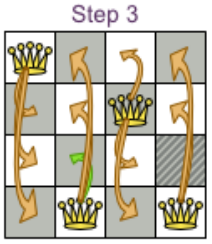
n: <= s * n^2 iterations

Selected moves for each step

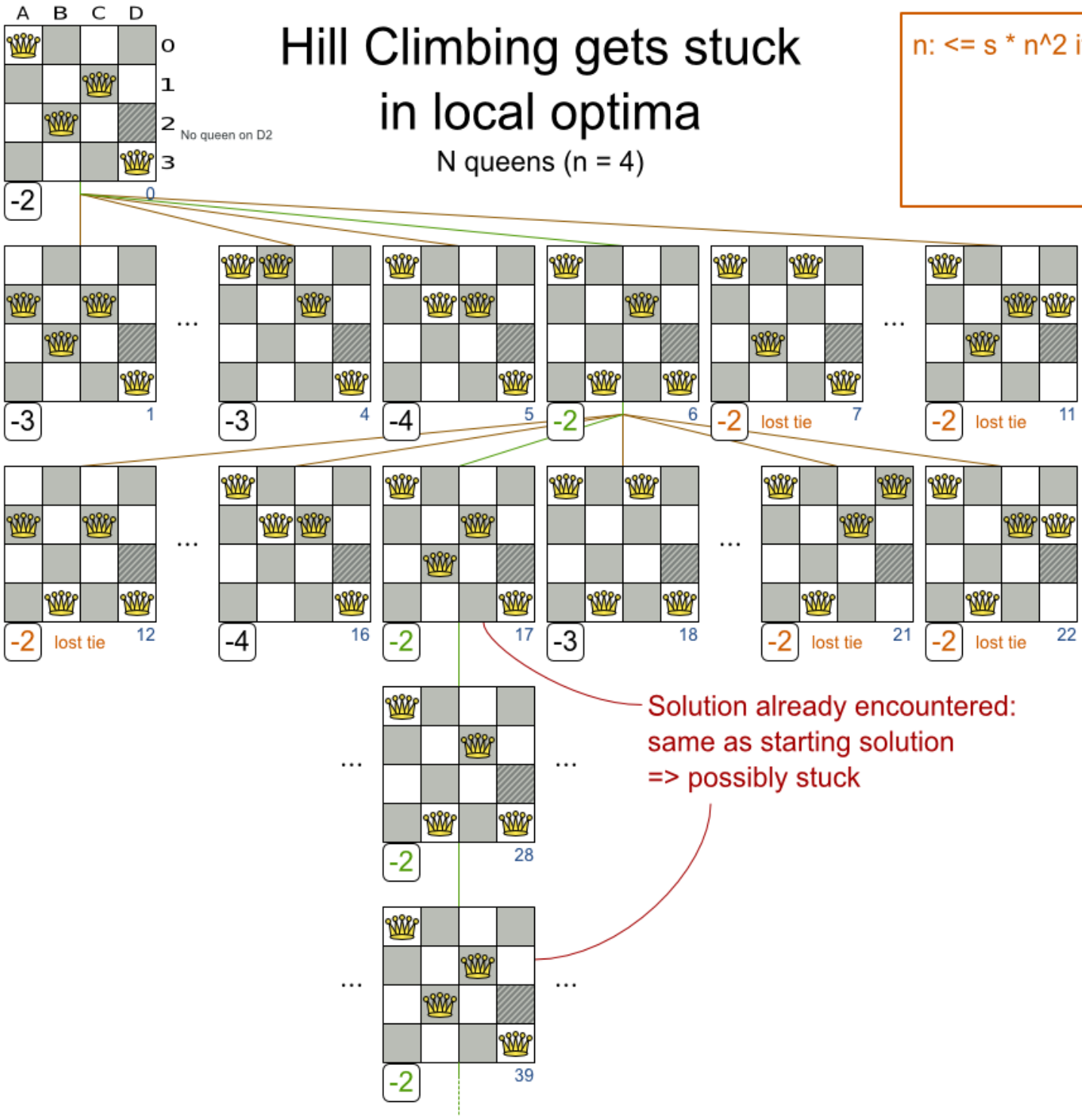




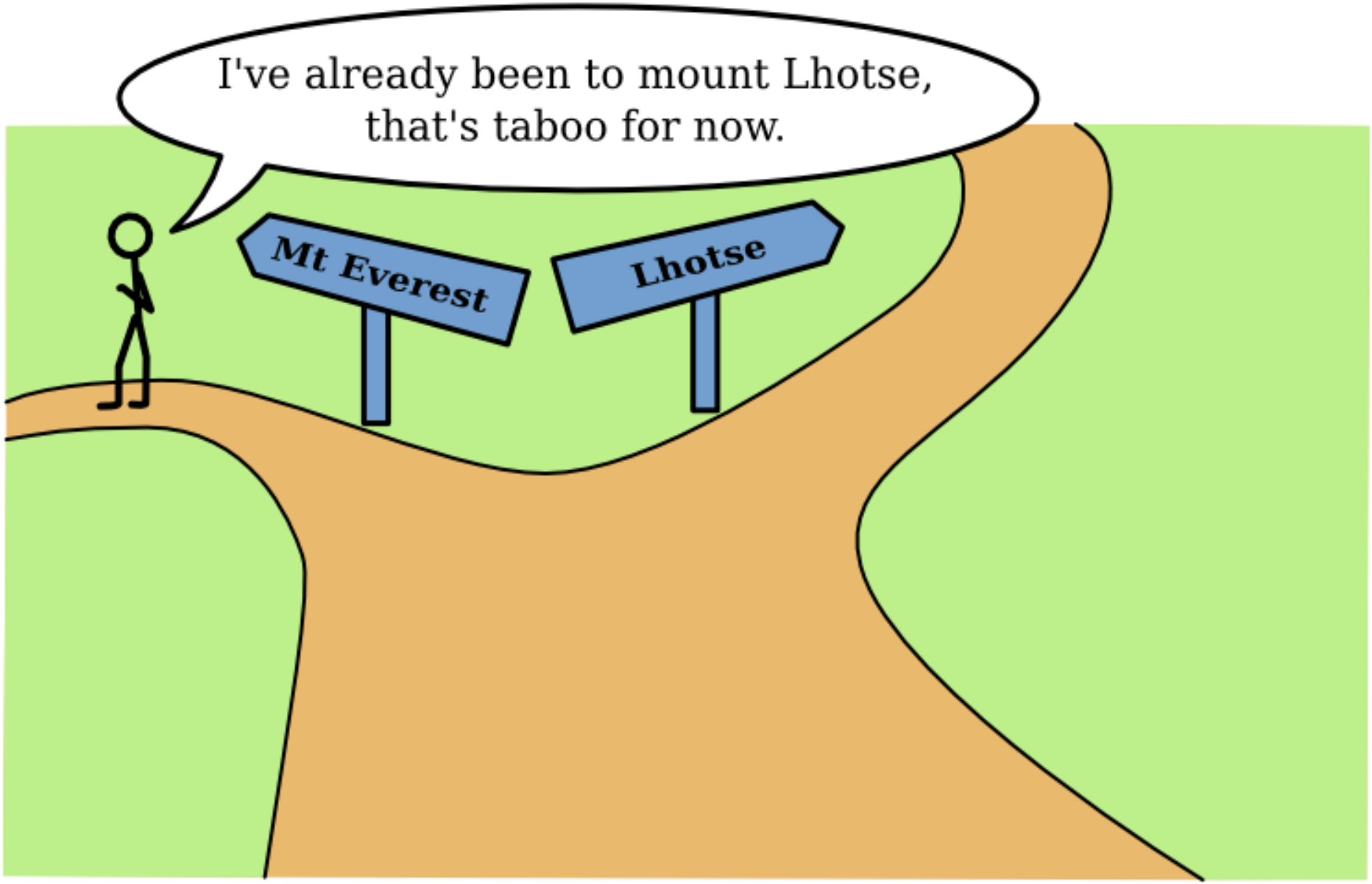




⋮



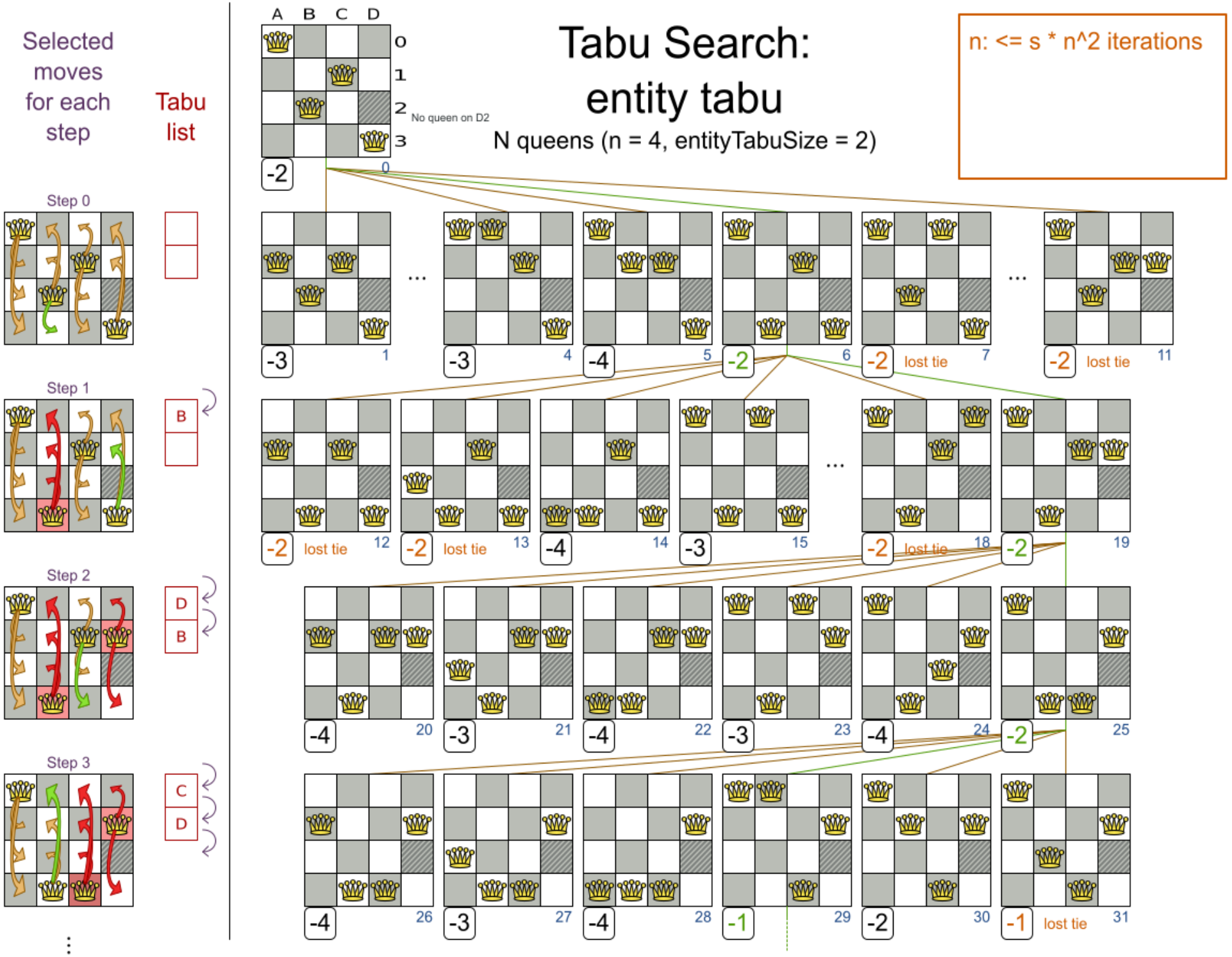
Tabu Search


I've already been to mount Lhotse,
that's taboo for now.
Mt Everest
Lhotse

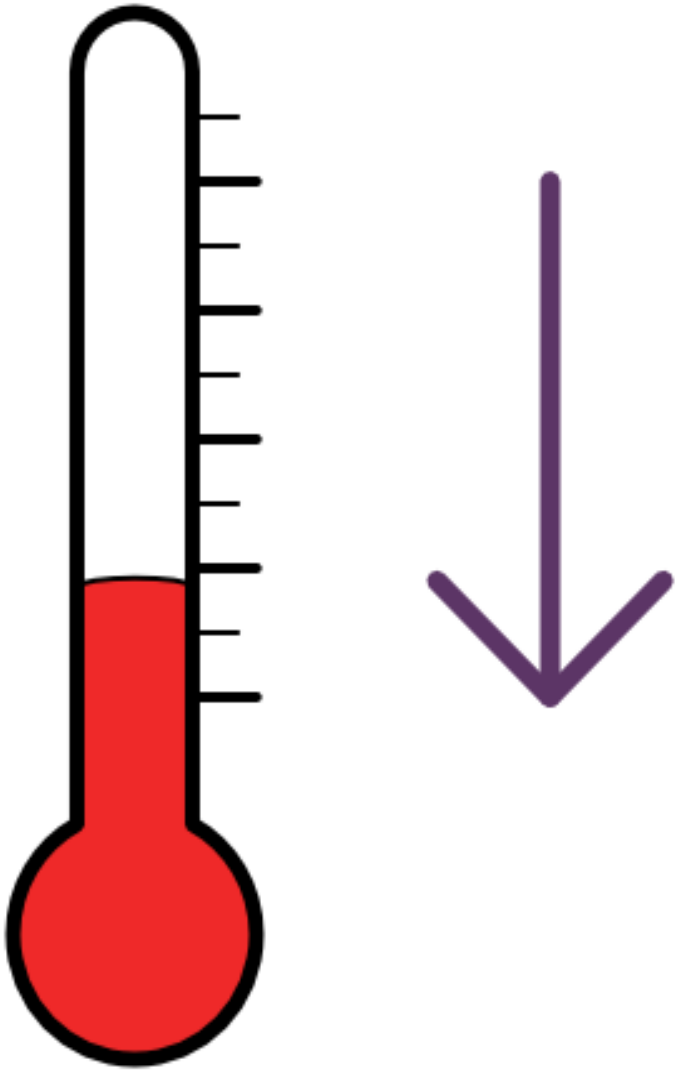
Tabu Search: entity tabu

N queens (n = 4, entityTabuSize = 2)

n: <= s * n^2 iterations



Simulated Annealing



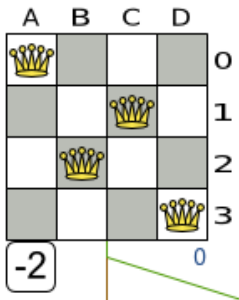
Simulated Annealing (time gradiant aware)

N queens (n = 4, startingTemperature = 2)

n: <= s * m iterations

Temperature decreases for each step

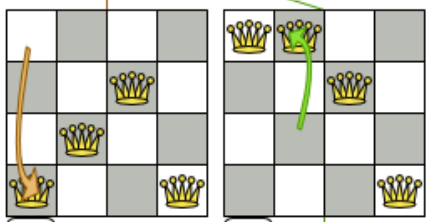
$\max = e^{\Delta/t}$



Step 0

t
2.0

Δ	max
≥0	any
-1	0.61
-2	0.37
-3	0.22
-4	0.14



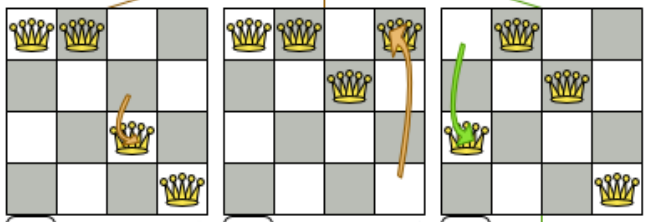
Δ = -2 ▢ = 0.41 > 0.37

Δ = -1 ▢ = 0.50 ≤ 0.61

Step 1

t
1.6

Δ	max
≥0	any
-1	0.54
-2	0.29
-3	0.15
-4	0.08



Δ = -1 ▢ = 0.88 > 0.54

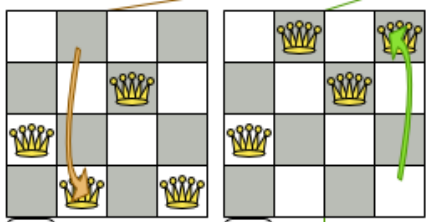
Δ = -2 ▢ = 0.31 >0.29

Δ = +2 ▢ = n/a ≤ any

Step 2

t
1.2

Δ	max
≥0	any
-1	0.43
-2	0.19
-3	0.08
-4	0.04



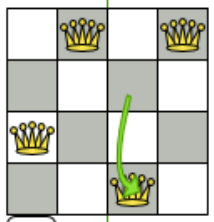
Δ = -1 ▢ = 0.74 > 0.43

Δ = -2 ▢ = 0.18 ≤ 0.19

Step 3

t
0.8

Δ	max
≥0	any
-1	0.29
-2	0.08
-3	0.02
-4	0.01

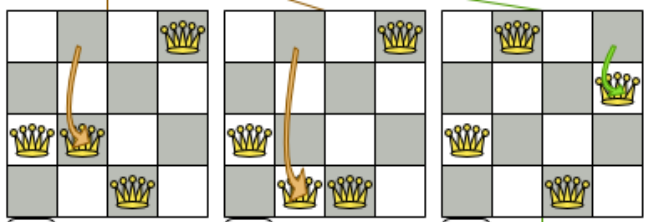


Δ = +2 ▢ = n/a ≤ any

Step 4

t
0.4

Δ	max
≥0	any
-1	0.08
-2	0.01
-3	0.00
-4	0.00



Δ = -2 ▢ = 0.97 > 0.01

Δ = -1 ▢ = 0.11 > 0.08

Δ = +1 ▢ = n/a ≤ any

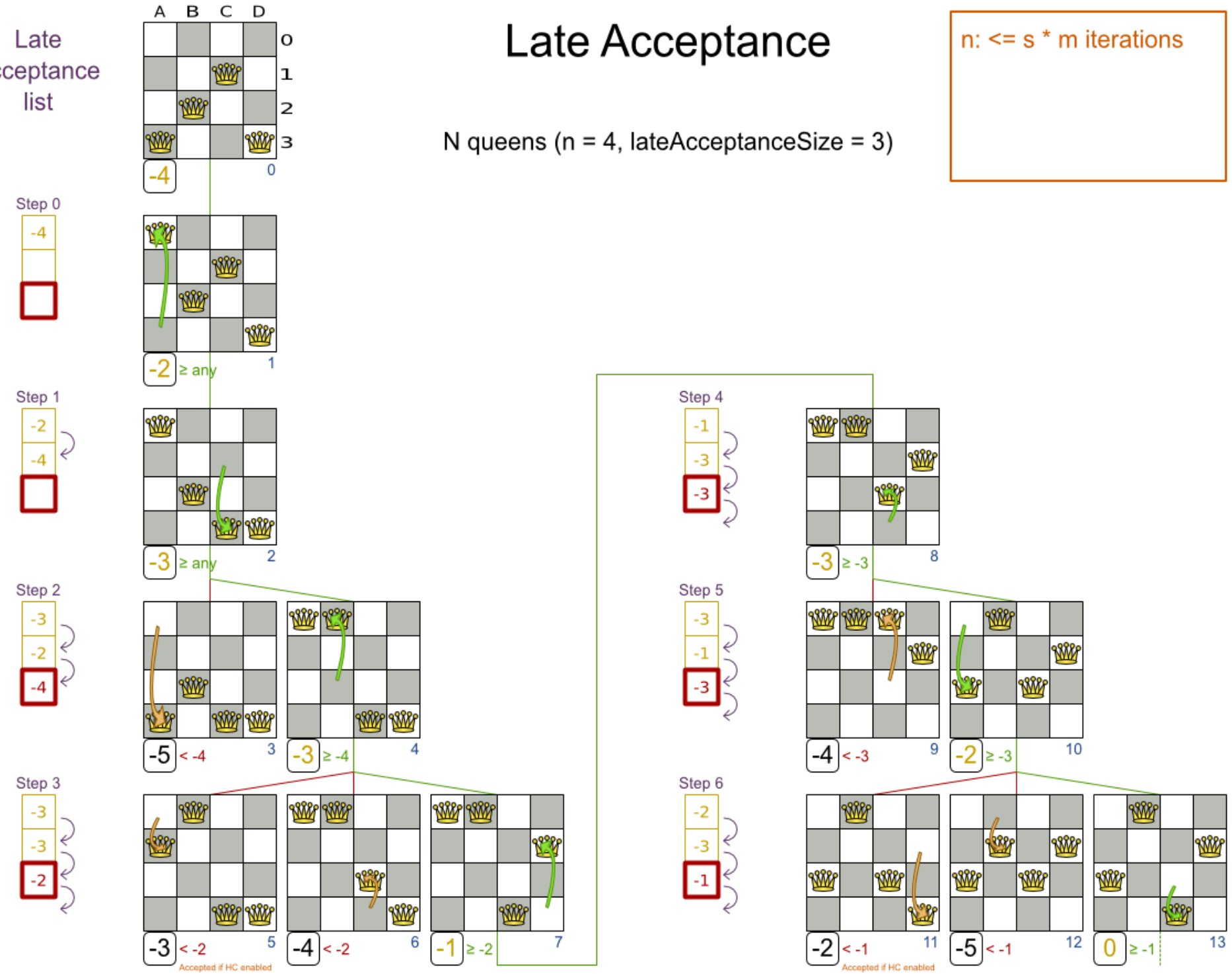
⋮

Late acceptance

Late Acceptance

N queens (n = 4, lateAcceptanceSize = 3)

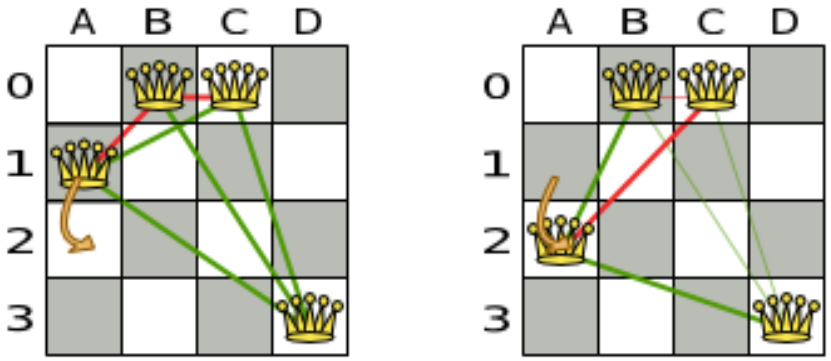
n: <= s * m iterations



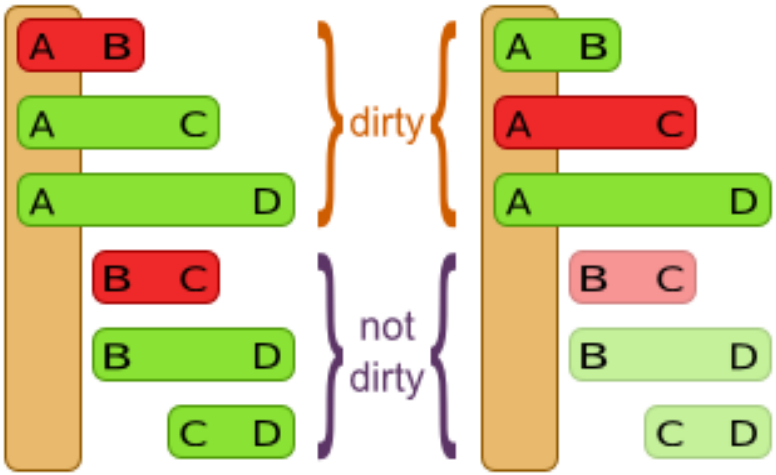
Performance tricks

Incremental score calculation

Incremental score calculation is much more scalable because only the delta is calculated.



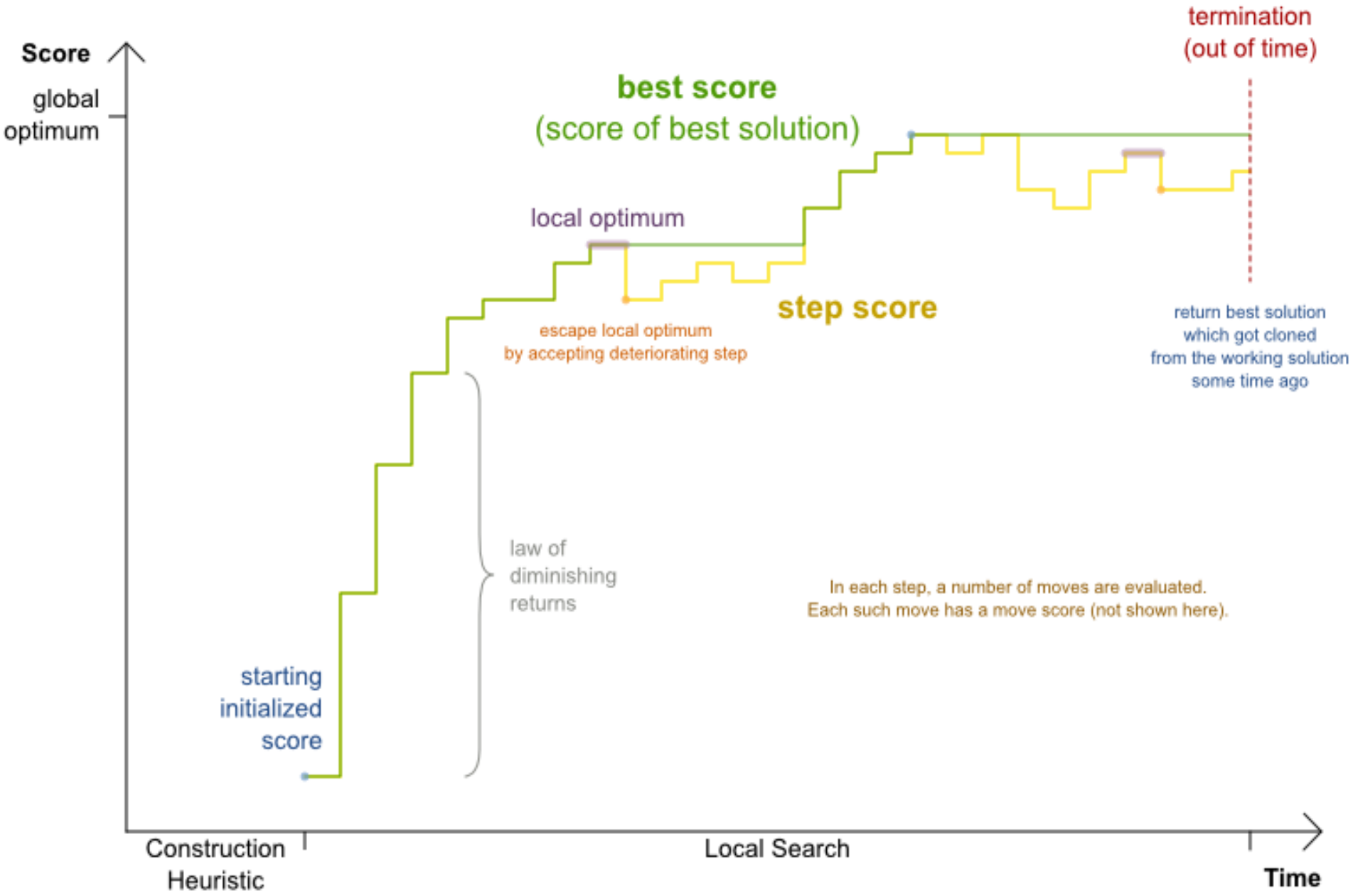
The rule engine
(with forward chaining)
only recalculates dirty tuples.



queens	dirty		total	speedup
4	3	of	6	time / 2
8	7	of	28	time / 4
16	15	of	120	time / 8
32	31	of	496	time / 16
64	63	of	2016	time / 32
n	*n-1*	*of*	*n*(n-1)/2*	time / *(n/2)*

Local Search score over time

In 1 Local Search run, do not confuse starting initialized score, best score, step score and move score.



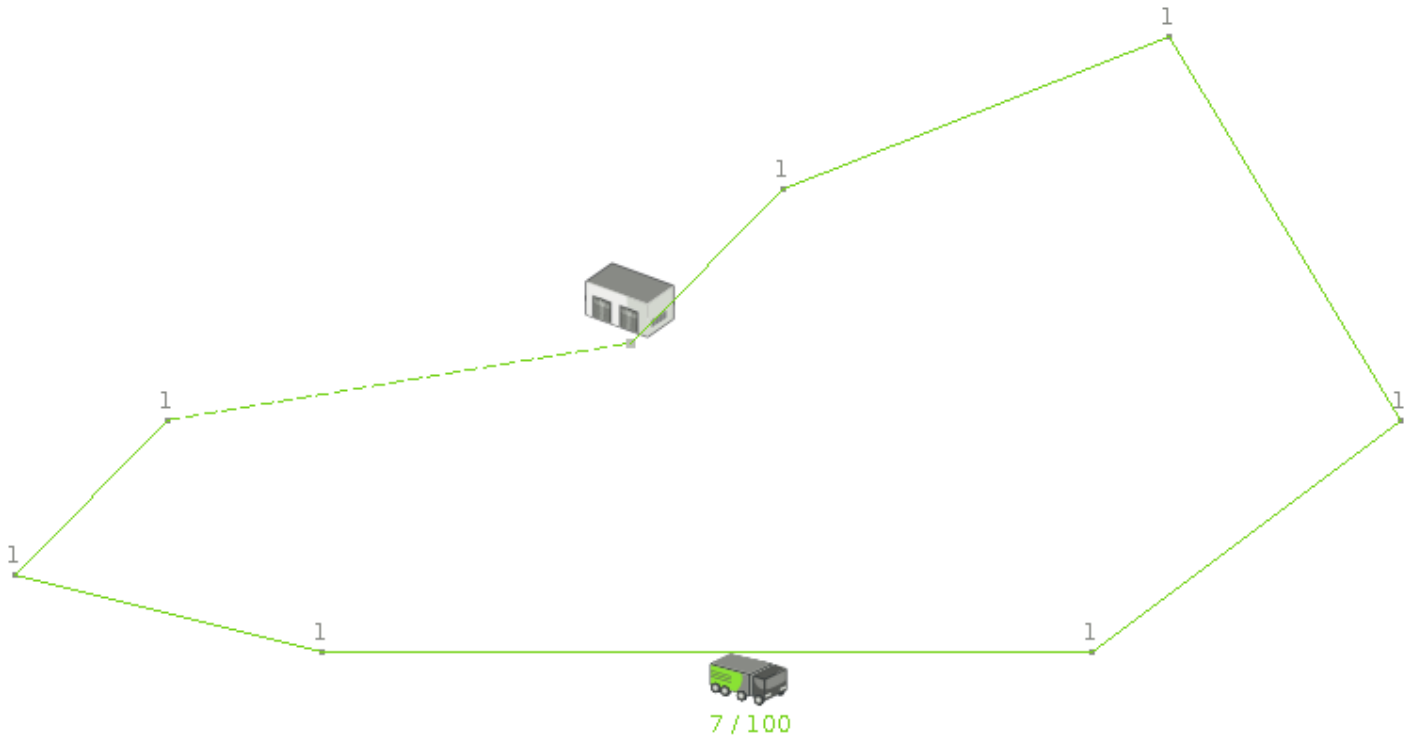
Reuse existing business code

```
public class Nurse {

  private Country country;

  public boolean isHoliday(Date date) {
    if (country == Country.BE) {
      // true if date is 1-JAN, easter monday, 21-JUL, ...
    } else if (country == Country.FR) {
      // true if date is 1-JAN, easter monday, 14-JUL, ...
    } else if (...) {
      ...
    }
    ...
  }

}
```



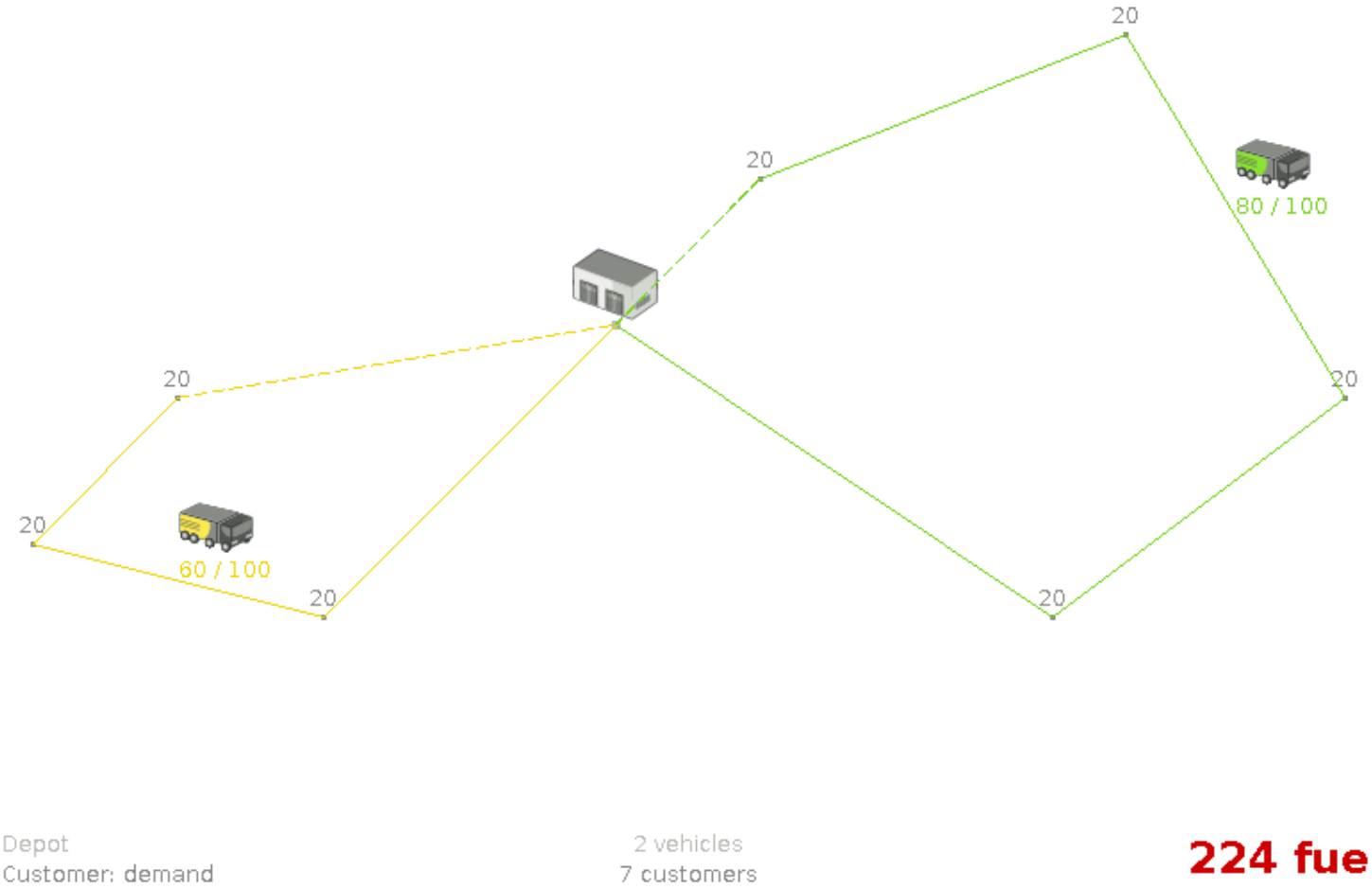
Depot
Customer: demand

2 vehicles
7 customers

210 fuel

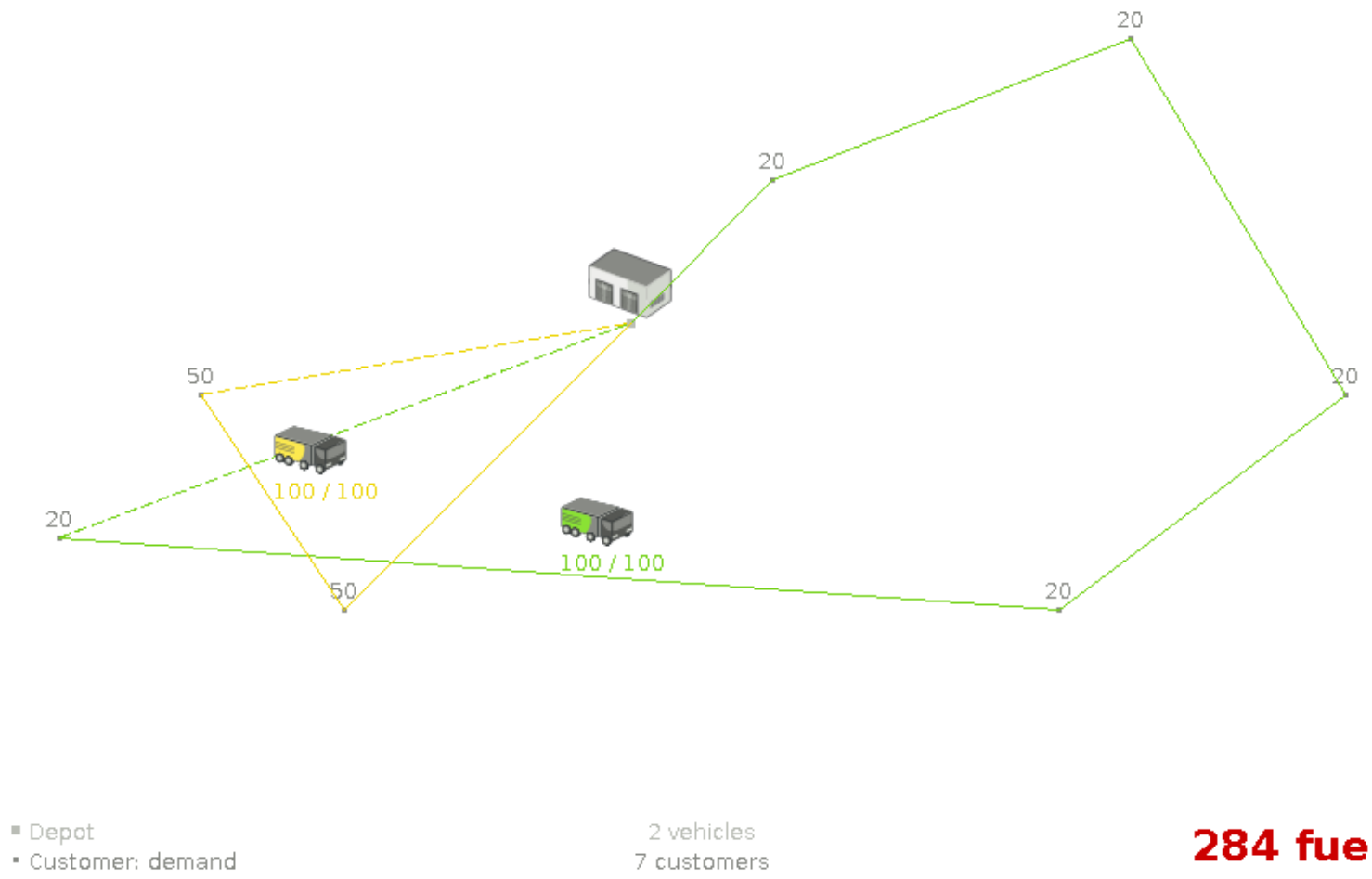
Assumption: **An optimal VRP route uses only 1 vehicle.**

Assumption: **An optimal VRP route uses only 1 vehicle. (false)**



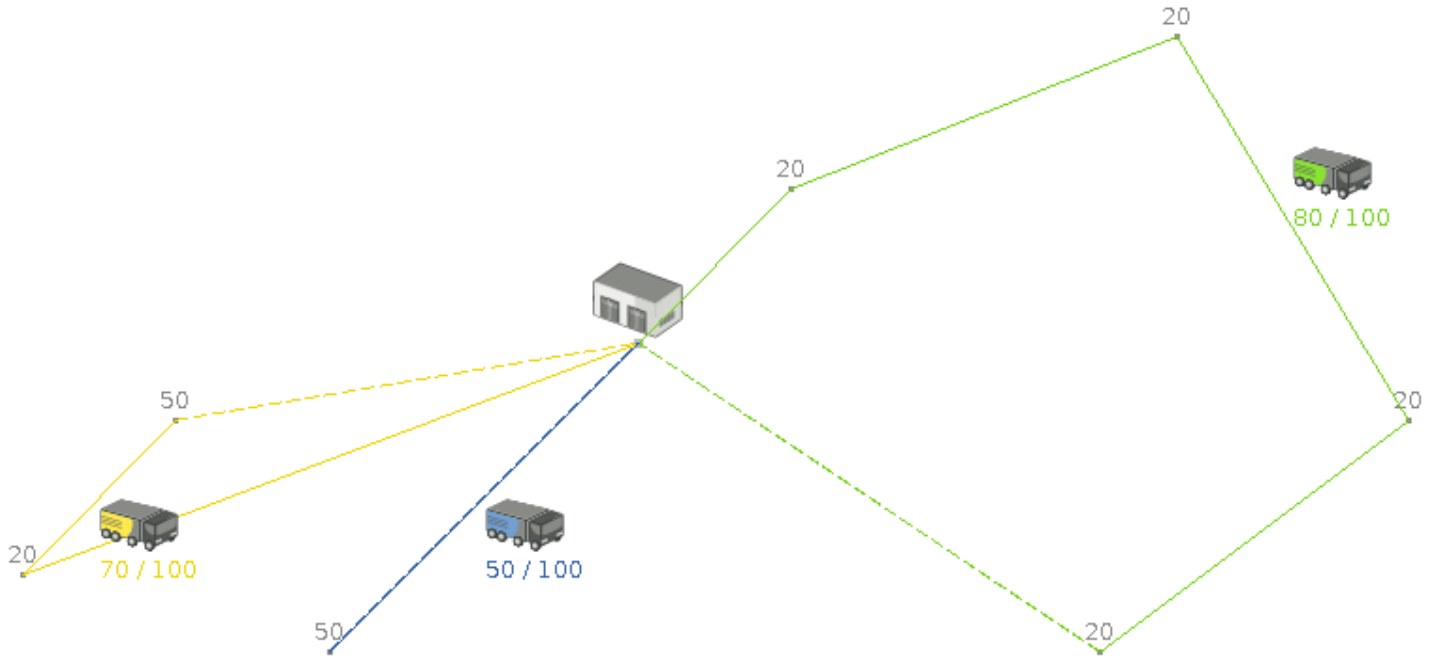
Assumption: **An optimal VRP route has no crossing lines.**

Assumption: **An optimal VRP route has no crossing lines. (false)**



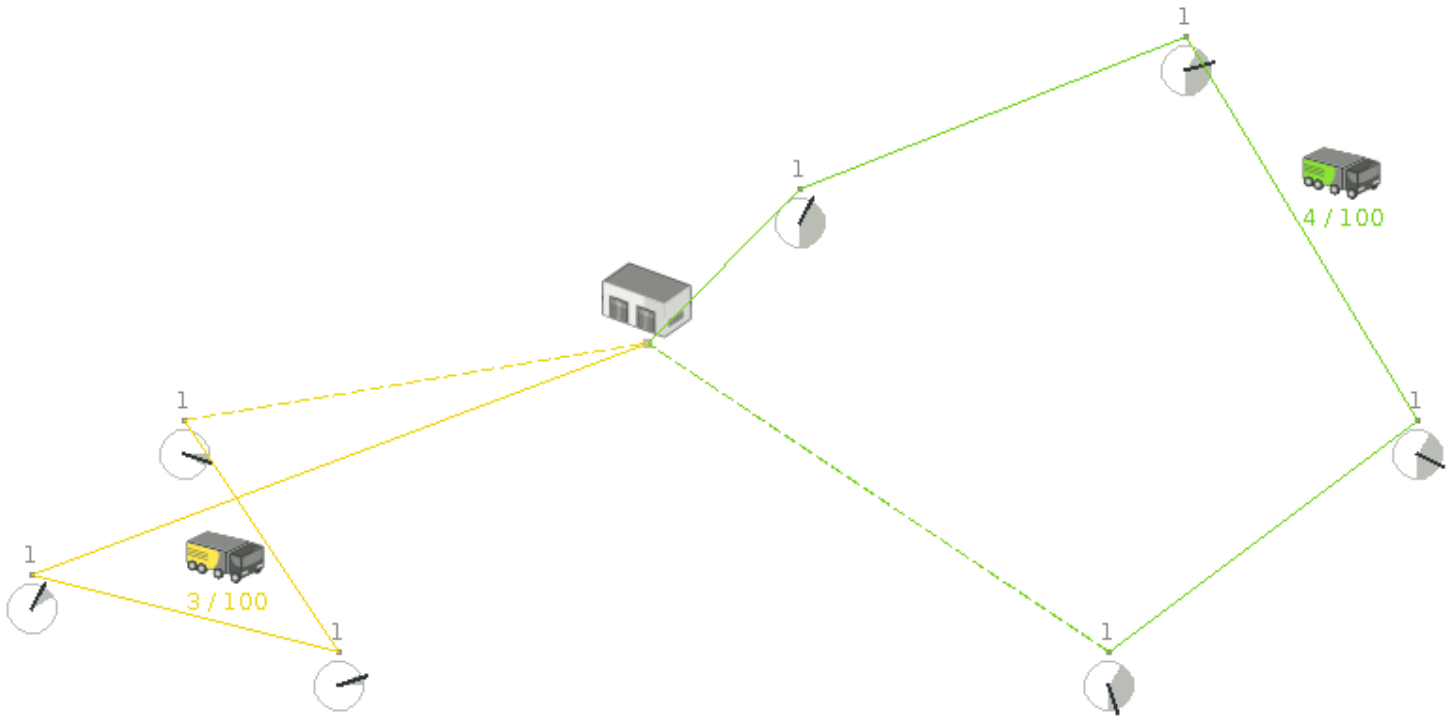
Assumption: **An optimal, feasible VRP route with n vehicles is still optimal for n+1 vehicles.**

Assumption: **An optimal, feasible VRP route with n vehicles is still optimal for n+1 vehicles. (false)**



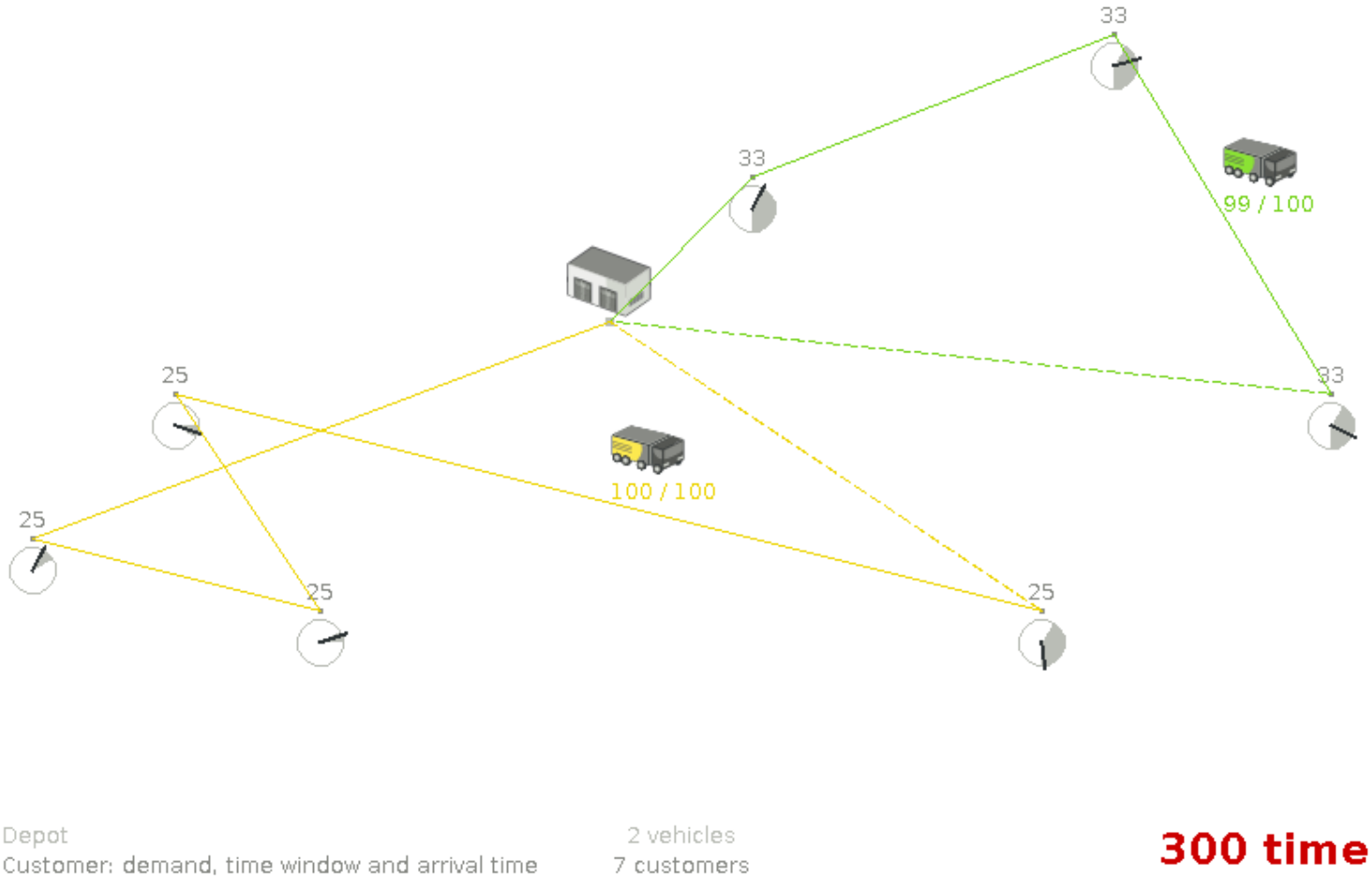
Assumption: **An optimal VRP route has no crossing lines of the same color.**

Assumption: **An optimal VRP route has no crossing lines of the same color. (false)**



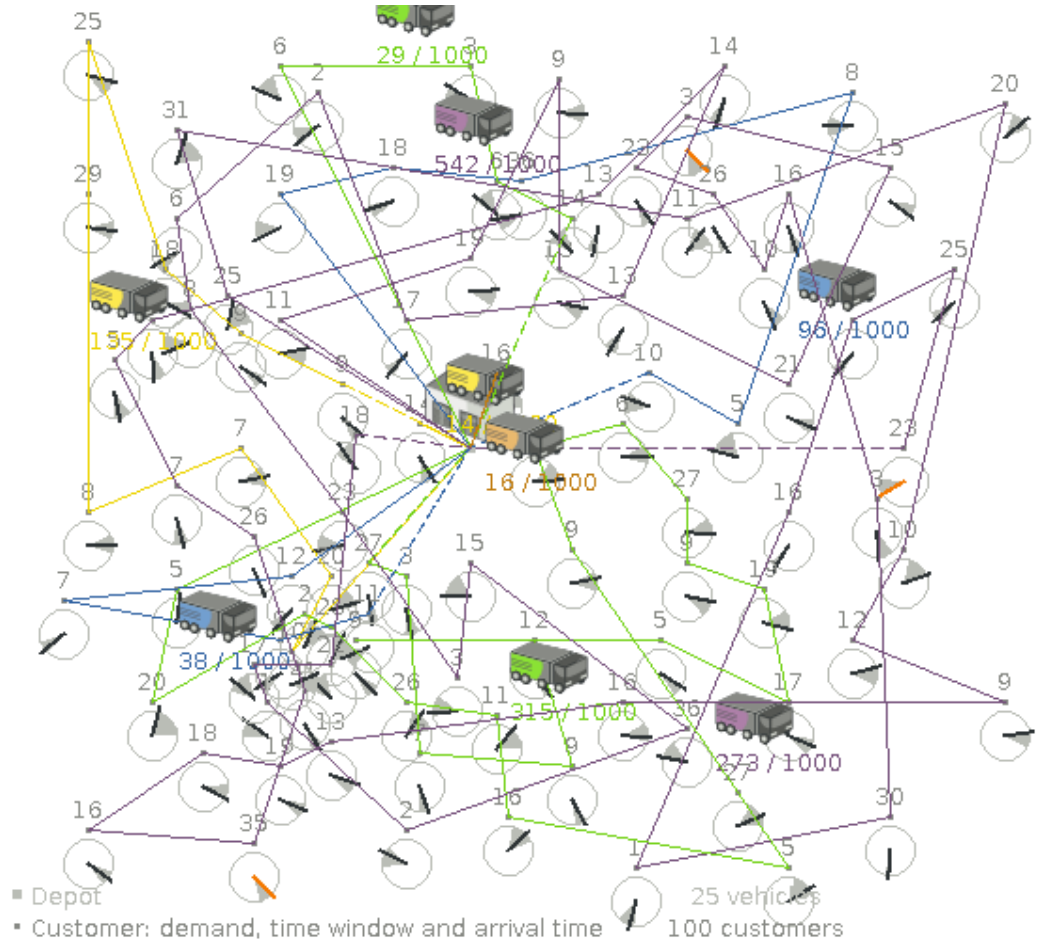
Assumption: **We can focus on time windows before focusing on capacity (or vice versa).**

Assumption: **We can focus on time windows before focusing on capacity (or vice versa). (false)**



Assumption: **Humans optimize VRP optimally.**

Assumption: **Humans optimize VRP optimally. (false)**

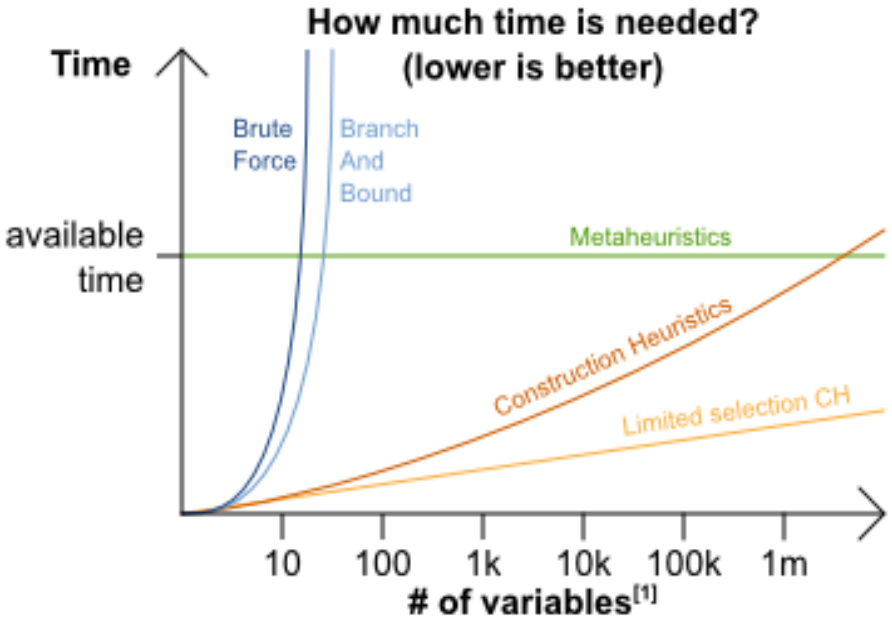


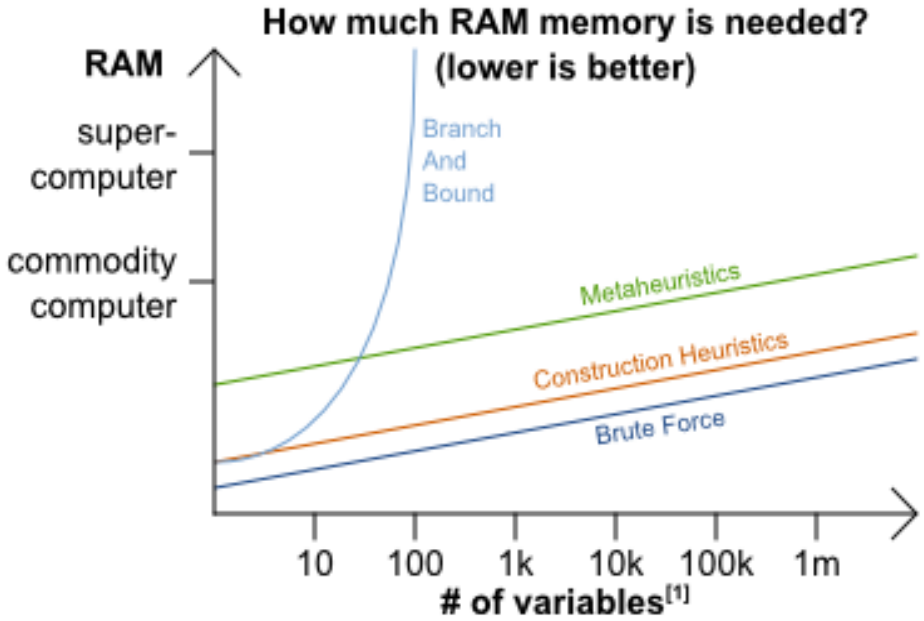
1,610 time

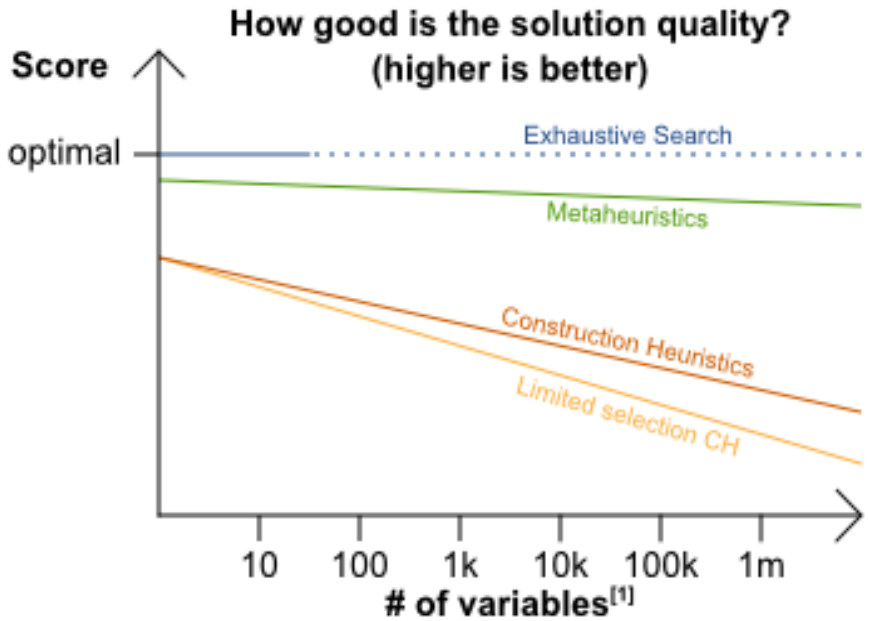
Can a manager reasonable judge if this is optimal?

Scalability of optimization algorithms

When scaling out, metaheuristics deliver the best solution in reasonable time on realistic hardware.







Effects of scaling out:

Exhaustive Search delivers the optimal solution but takes forever.

Construction Heuristics (including greedy algorithms) deliver poor quality in time.

Metaheuristics deliver good quality in time.

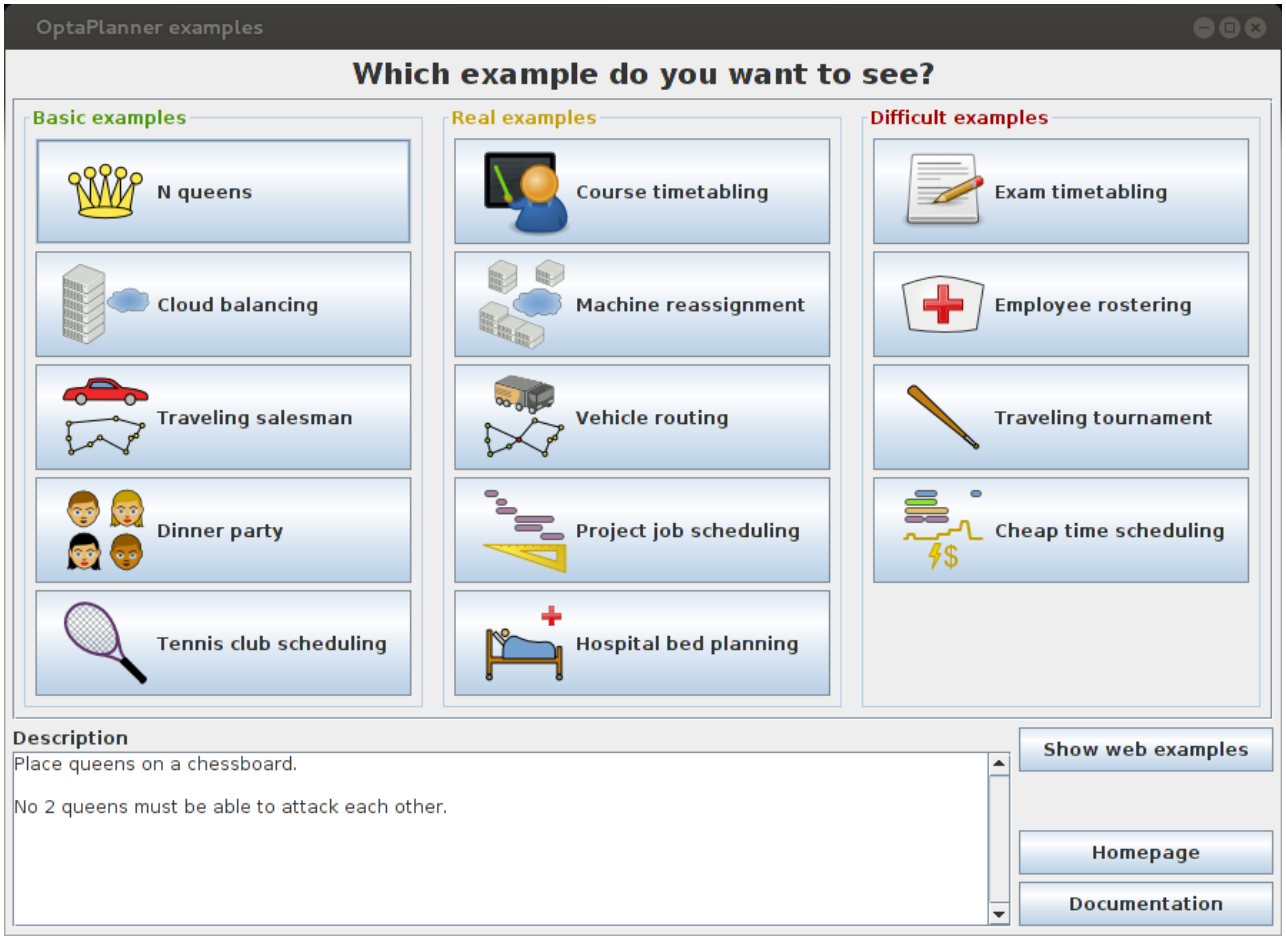
Note: Metaheuristics include a CH to initialize.

This is a rough generalization, based on years of experience and a large number of benchmarks on realistic use cases. Results may differ per use case and per solver configuration.

[1] Vars with a large value range (binary vars scale much more)

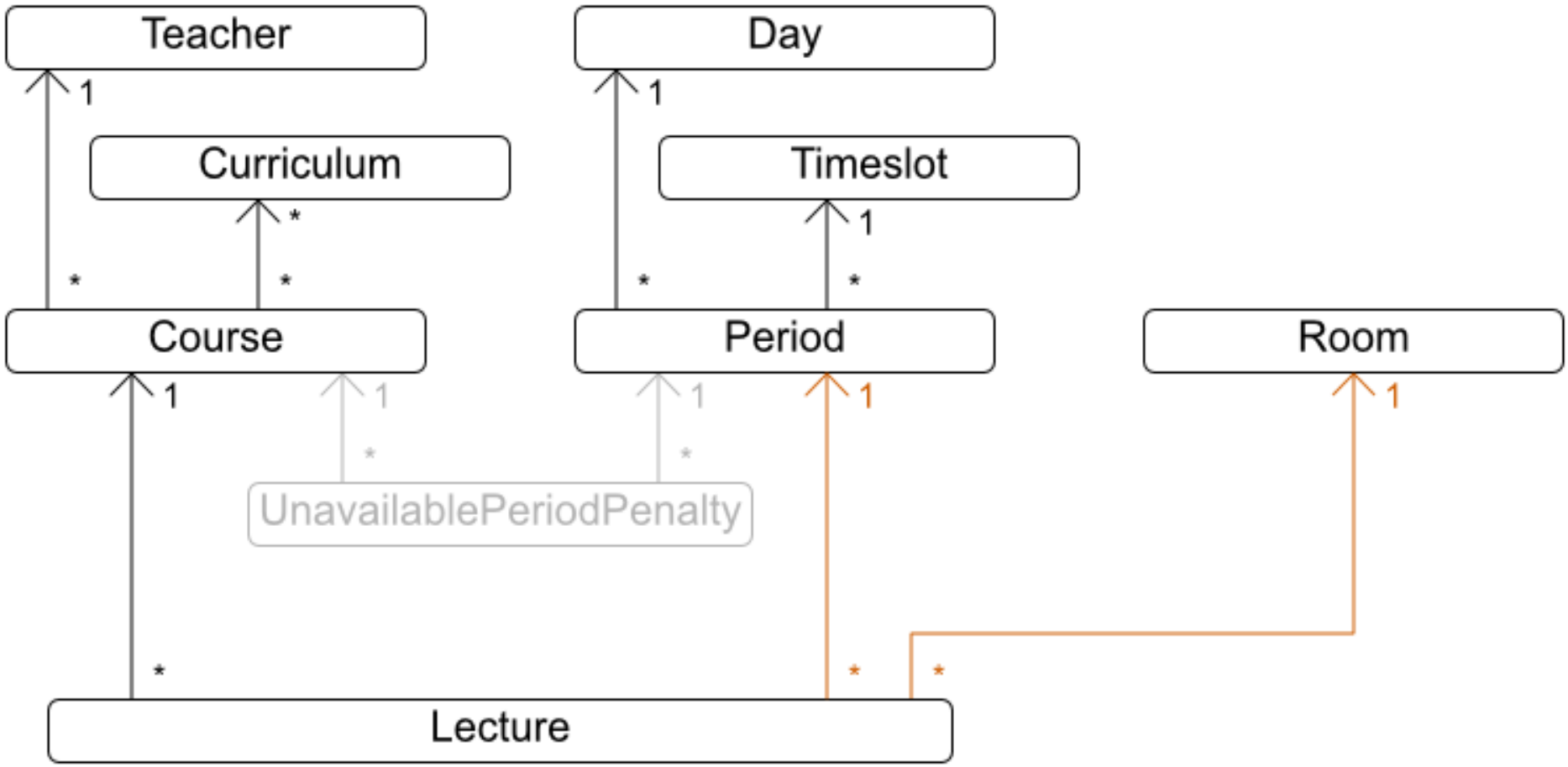
Who’s in control?

The user is in control



Course scheduling demo

Curriculum course class diagram



Teacher, Course, Room

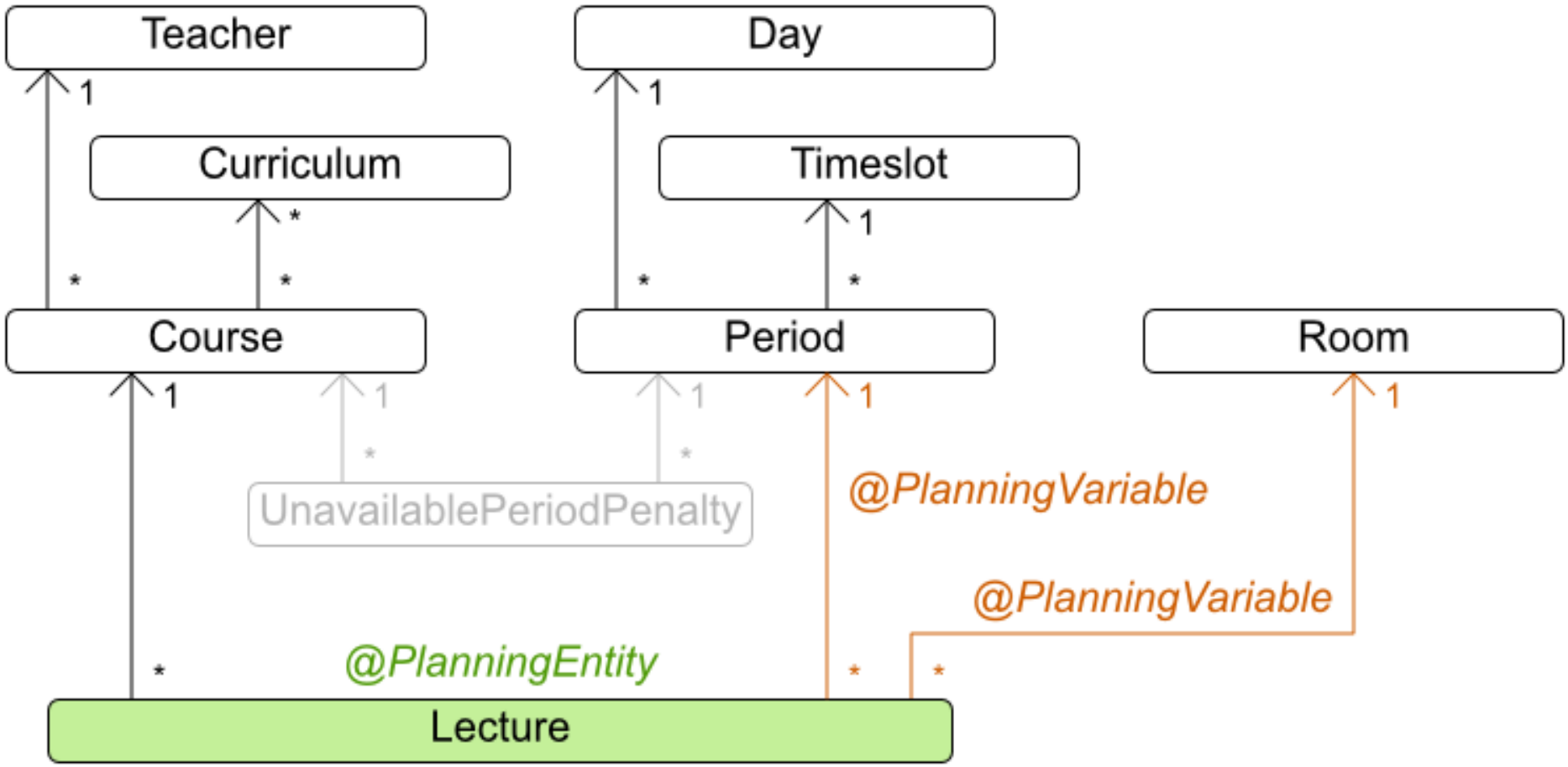
```
class Teacher {
  ...
}

class Course {
  Teacher teacher;
  ...
}

class Period {
  ...
}

class Room {
  ...
}
```

Curriculum course class diagram



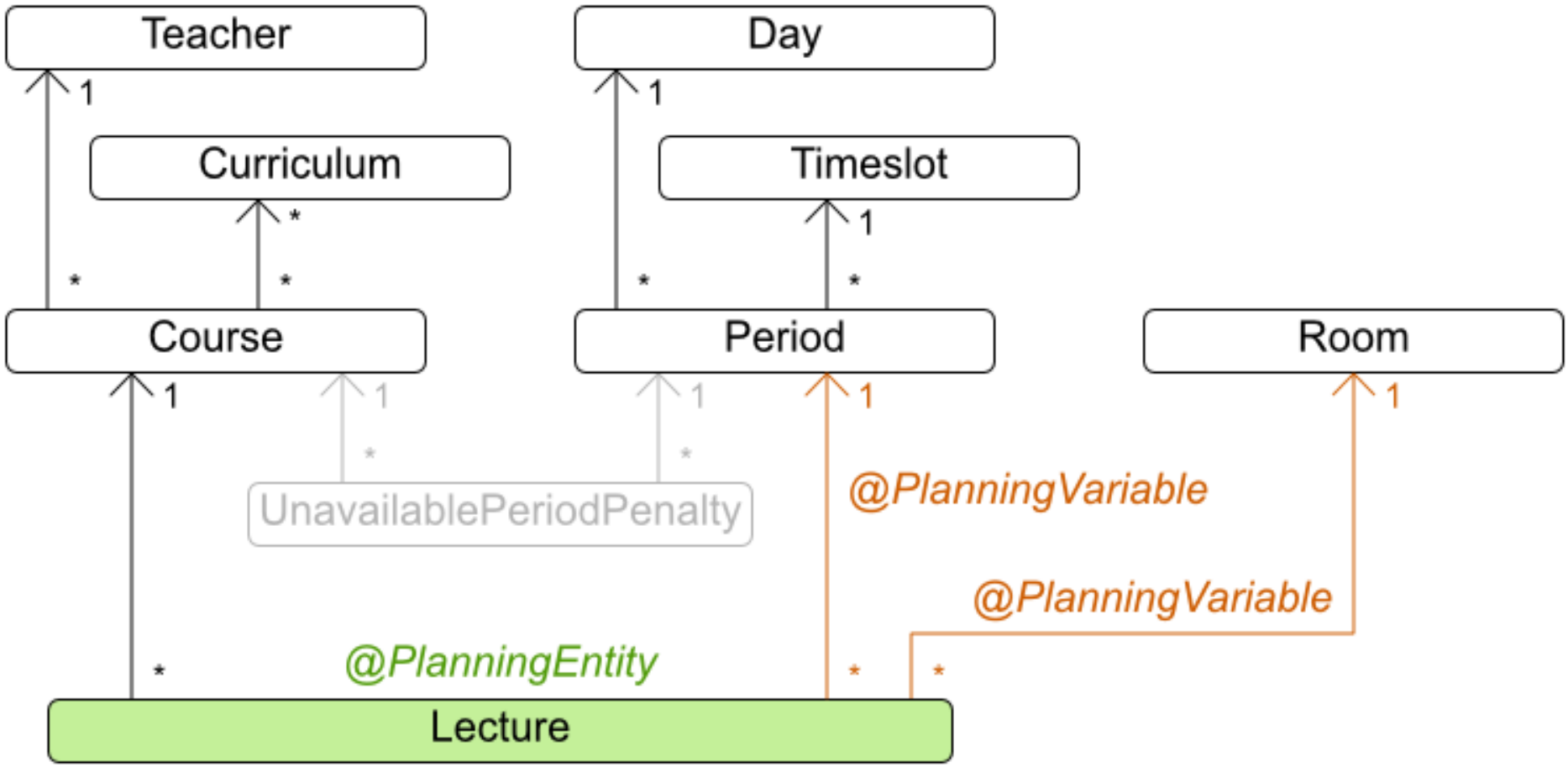
Lecture

```
@PlanningEntity
class Lecture {
  Course course;
  int lectureIndexInCourse;

  @PlanningVariable(...) Period period;
  @PlanningVariable(...) Room room;
  ...
}
```

Add a constraint

Curriculum course class diagram



With Java

```
class UnavailablePeriodPenalty {
  Course course;
  Period period;
  ...
}

public HardSoftScore calculateScore(Schedule schedule);
  int hardScore = 0;
  for (UnavailablePeriodPenalty penalty : schedule.getPenaltyList()) {
    for (Lecture lecture : schedule.getLectureList()) {
      if (penalty.getCourse() == lecture.getCourse()
          && penalty.getPeriod() == lecture.getPeriod()) {
        hardScore--;
      }
    }
  }
  ...
  return HardSoftScore.valueOf(hardScore, softScore);
}
```

With Drools rule engine

```
class UnavailablePeriodPenalty {
  Course course;
  Period period;
  ...
}

rule "unavailablePeriodPenalty"
  when
    // When a course is unavailable for a certain period ...
    UnavailablePeriodPenalty($c : course, $p : period)
    // ... and a lecture of that course is scheduled in that period ...
    Lecture(course == $c, period == $p)
  then
    // ... then we lose 1 hard score point
    scoreHolder.addHardConstraintMatch(kcontext, -1);
end
```

Q & A

- OptaPlanner homepage
  - http://www.optaplanner.org (http://www.optaplanner.org)
- Reference manual
  - http://www.optaplanner.org/learn/documentation.html (http://www.optaplanner.org/learn/documentation.html)
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